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Investigation of Collision Performance Prediction Method for Anti-Collision Beam Based on MI-MDA-Stacking Algorithm

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Keywords：anti-collision beam, frontal collision, ensemble learning, surrogate.

ABSTRACT

To optimize computing resources and reduce labor costs associated with finite element analysis in the traditional anti-collision beam design process, constructing a vehicle collision surrogate model has emerged as an efficient and feasible method for predicting collision performance. In order to enhance the prediction accuracy of the surrogate model, a model selection strategy based on mutual information theory and the random forest algorithm for the stacking algorithm is proposed. High-precision surrogate models are developed for estimating both maximum collision acceleration and maximum compression of the anti-collision beam structure during collisions. Firstly, the fundamental principles of mutual information and random forest are introduced, and the algorithm framework is proposed. Secondly, the validity of the algorithm is validated by using mathematical test functions. Finally, the proposed algorithm is employed to construct high-precision surrogate models that accurately predict collision performance for the anti-collision beam. The results demonstrate that these constructed surrogate models enable quick and accurate predictions of anti-collision beam performance during collisions. This research holds significant engineering implications for enhancing safety designs in vehicle structures.

INTRODUCTION

With the continuous advancement of China's economy, there has been a significant surge in the number of vehicles. However, this phenomenon has also led to an alarming increase in traffic accidents, resulting in substantial losses to both human lives and property. In order to mitigate the impact of these accidents on society, both the government and major automobile manufacturers have increasingly prioritized automotive safety and conducted extensive research in this field. Different collision scenarios can be categorized into various forms such as frontal collisions, side collisions, and tailgating incidents, among others. As depicted in Figure 1, frontal collisions constitute a considerable proportion of traffic accidents. During a frontal collision, the anti-collision beam serves as a pathway for transmitting the collision load to both the crash box and front longitudinal beam. In this process, the collapse deformation of the crash box effectively absorbs collision energy, thereby mitigating passenger injuries caused by impact forces. Consequently, accurate prediction of vehicle collision performance plays a pivotal role in optimizing the design of anti-collision beam structures."

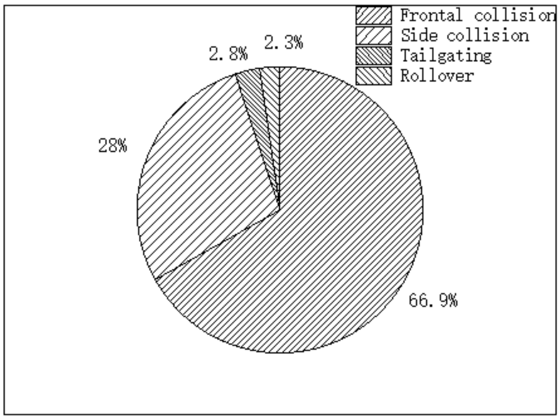

Fig. 1. The Proportion of Different Vehicle Collision Forms.

To enhance the efficiency of vehicle collision performance prediction, the surrogate model technique is proposed. This technique establishes a mapping relationship between design variables and output response by mathematically modeling simulation results from finite sample points, thereby approximating the simulation model (Chen et al.,

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2022). Lu (2021) investigated the influence of vehicle front cabin components on energy absorption during collisions and developed Kriging, response surface, and radial basis models respectively. The NSGA-II algorithm was employed for iterative optimization to enhance vehicle collision safety performance. Arne Kaps et al. (2022) introduced an optimization scheme based on the hierarchical Kriging method to address dimension optimization in side collisions and shape optimization in front collisions, achieving computational cost reduction while maintaining accuracy. Zhang (2019) proposed a bionic anti-collision beam structure which was optimized using response surface method and multi-objective optimization approach to obtain optimal structural size parameters for the bionic anti-collision beam. Therefore, employing surrogate techniques instead of finite element simulations can significantly improve optimization efficiency during engineering processes.

However, due to the highly nonlinear nature of the vehicle collision process and the limitations of traditional surrogate models in meeting engineering design requirements, ensemble learning has emerged as a branch of machine learning that combines multiple base models using specific combination strategies to achieve higher prediction accuracy compared to individual models. In recent years, there has been extensive research on employing ensemble learning methods for complex engineering problems. For instance, Yang et al. (2023) utilized a genetic algorithm to adaptively combine five prediction models and successfully constructed an ensemble model for predicting the structural mechanical characteristics curve of the vehicle collapse zone with sufficient accuracy. Zhang (2019) proposed an origami structure crash box and employed the XGBoost algorithm to predict parameters such as energy absorption per unit mass, average collision force, and mass of the box. Tang et al. (2017) introduced a data-driven train collision modeling method that extracted force-displacement curve models from finite element simulation data using parallel random forest algorithms to predict collision velocity under given conditions. These studies collectively demonstrate the feasibility of utilizing ensemble learning techniques for constructing more precise surrogate models for vehicle collisions.

The stacking algorithm is an algorithmic framework rooted in the concept of ensemble learning (Wolpert, 1992). Diverging from other ensemble learning algorithms that employ averaging or weighting techniques to combine models, the stacking algorithm leverages the prediction results of the base model as features for training a second-layer meta model and utilizes the output of this meta model as the final prediction results. Given that different algorithmic models exhibit varying degrees of fitting effectiveness on diverse datasets, it becomes crucial to carefully select a base model with high prediction accuracy and low correlation when training the stacking model. Yan et al. (2022) proposed a pest bird density prediction method based on the stacking algorithm for addressing bird damage faults on transmission lines, where they evaluate the relevance of each base model using Pearson's coefficient. Shi et al. (2023) introduced a diversity regularized stacking algorithm for power load forecasting and employed mutual information and hierarchical clustering algorithms to select combinations of base models with low relevance, thereby demonstrating superior forecasting performance compared to traditional ensemble models or single models.

Despite the widespread application of stacking algorithms across various domains, their utilization in predicting the collision performance response of anti-collision beams remains limited. To address this gap, we propose a model selection strategy for the stacking algorithm in this paper, referred to as MI-MDA-Stacking, which incorporates importance evaluation indicators from the random forest algorithm and mutual information. This approach comprehensively considers the correlation and significance of the base models. By employing the proposed method, a highly accurate surrogate model is constructed for assessing the collision performance of anti-collision beam structures, thereby replacing computationally intensive finite element simulations.

MI-MDA-STACKING ALGORITHM

Mutual Information

The concept of mutual information (MI) quantifies the informational content carried by one random variable with respect to another random variable, as demonstrated in Eq. 1.

$$I(X;Y)=\int_Y\int_X p(x,y)\lg\left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{1}$$

where $p(x,y)$ is the joint probability density function of X and Y, while $p(x)$ and $p(y)$ is the marginal probability density functions of X and Y, respectively. The mutual information value can measure the correlation between two random variables (Liu et al., 2012). The correlation of the base models of the stacking algorithm can be evaluated based on the mutual information.

Random Forest Feature Importance Assessment

The random forest algorithm is an ensemble method based on the decision tree algorithm, where random feature selection is incorporated during the training process of the decision tree (Breiman, 2001). Random forest provides two measures for assessing feature importance: mean decrease impurity (MDI) and mean decrease accuracy (MDA).

During the training process of random forest, multiple decision trees are generated by selecting features and dividing them based on specific feature values. To assess the contribution of each feature to model prediction accuracy, their importance can be measured by calculating the average reduction in impurity achieved during tree generation (Du et al., 2019). However, when dealing with correlated features, this approach is susceptible to bias introduced by the order of feature selection. Consequently, only initially selected features tend to receive higher importance scores while other correlated features may appear less important. As a result, the Mean Decrease Impurity (MDI) method does not accurately represent true feature contributions to model accuracy. To address this limitation and obtain more precise measurements of individual feature influence on prediction accuracy, we propose using the Mean Decrease Accuracy (MDA) method. The MDA method involves perturbing feature values with random numbers and quantifying resulting decreases in model prediction accuracy. Larger decreases indicate greater influence and higher importance for that particular feature. In comparison to MDI, MDA provides a more direct measure of individual feature impact on model accuracy and better reflects their relative importance.

Algorithmic framework

The algorithmic framework proposed in this paper is illustrated in Fig. 2. Firstly, a set of base models comprising multiple types of algorithms is selected based on the training principles of different algorithms, and each base model is trained separately using the dataset for prediction purposes. Subsequently, mutual information values between models are computed by considering the prediction errors of the base models. The predicted values from these base models are then utilized as features to train a random forest model, which is randomly perturbed to assess the reduction in prediction accuracy for each feature and rank their importance accordingly. Next, the base model with the highest accuracy is chosen as well as another base model with low correlation to it based on mutual information measures. Additionally, any base model exhibiting small or even negative MDA (mean decrease accuracy) values is filtered out so that a set of highly accurate and minimally correlated combinations of base models can be obtained. Finally, these selected combinations are employed to train a stacking model; however, since all the chosen combinations consist of strong models, it becomes crucial to prevent overfitting by selecting a simpler meta-model such as a linear regression algorithm for this purpose. During the training phase, the meta-model's training set is generated using the leave-one-out method wherein unused samples from training data of individual base models are used to create training samples for the meta-model.

Model Evaluation

Upon completion of training the machine learning model, it is imperative to assess its performance using appropriate evaluation metrics. Model evaluation constitutes a crucial aspect of machine learning as it accurately reflects the level of fit between the model and dataset, enabling an objective assessment of its efficacy. In regression tasks, commonly employed evaluation metrics encompass RMSE (root mean square error), MAE (mean absolute error), and R-squared (coefficient of determination), which are mathematically expressed in Eq. 2-4.

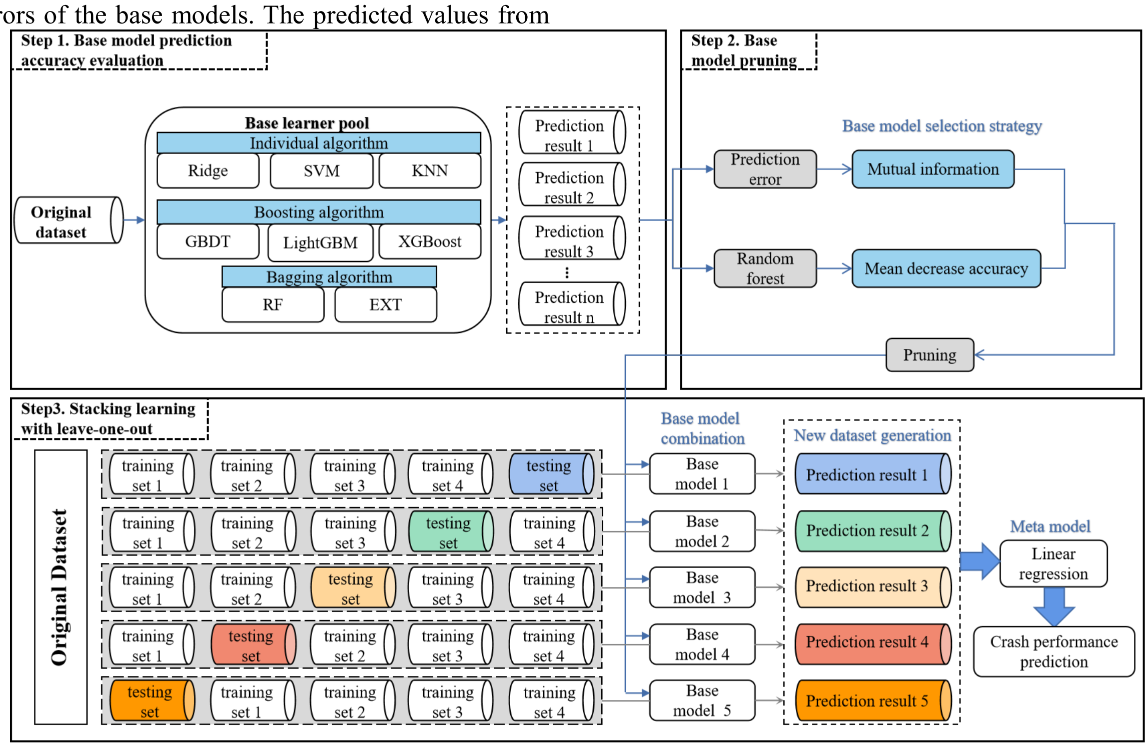

Fig. 2. MI-MDA-Stacking algorithm framework.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(Y_i - f(x_i))^2} \quad (2)$$

$$MAE = \sum_{i=1}^{n}\left|Y_i - f(x_i)\right| \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - f(x_i))^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \quad (4)$$

Among them, RMSE and MAE have the same dimension and can both quantify the discrepancy between the predicted value and the true value. However, they differ in that MAE reflects the absolute error while RMSE is more sensitive to outliers, thus indicating a smaller maximum error. R-squared denotes the goodness of fit of the predicted value to the true value, with an optimal value of 1. In terms of prediction models, lower values for both RMSE and MAE correspond to higher proximity of R-squared to 1, signifying reduced prediction errors and enhanced accuracy.

ALGORITHM VALIDATION

The algorithm proposed in this paper is validated in this section using mathematical test functions, as presented in Tbl. 1. The test functions are sampled using the Latin hypercube sampling method, with a sample size of 1000.

Integration Performance Analysis

In three separate test functions, each base model and the stacking ensemble model are trained individually. The performance of the models is evaluated using R-squared, and the results are presented in Fig. 3.

It is evident from Fig. 3 that different algorithms exhibit varying degrees of fit with different datasets, highlighting the importance of selecting appropriate algorithms for specific datasets. Compared to single models such as Ridge, SVM, and KNN, ensemble models like GBDT, LightGBM, and XGBoost demonstrate higher prediction accuracy and superior performance across diverse datasets, underscoring the effectiveness of ensemble learning methods in enhancing model performance. Amongst the three test functions, the stacking algorithm achieves the highest prediction accuracy due to its ability to combine not only with single models but also with other ensemble models. Thus, constructing a high-precision surrogate model based on the stacking algorithm proves to be effective.

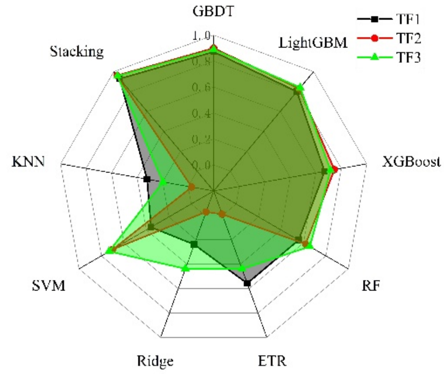

Fig. 3. Comparison of R_squared for each model in different test functions.

Analysis of Model Selection Strategies

In order to validate the efficacy of the model selection strategy proposed in this study, a surrogate model was developed using the MI-MDA-Stacking algorithm and compared with alternative strategies. The prediction errors of the models are presented in Tbl. 2, where A1, B1, and C1 represent base model combinations selected based on the MI-MDA-Stacking algorithm, while A2, A3, B2, B3, C2, and C3 denote base model combinations chosen by other strategies.

From the table, it is evident that the model selection strategy affects the predictive accuracy of the models. The predictive accuracy of the base models selected in combination A3, B3, and C3 is low which consequently leads to relatively lower predictive accuracy of their combined stacking models. This suggests that the accuracy of base models directly influences the predictive accuracy of stacking models. On the other hand, the combination of A2, B2, and C2 is selected based on predictive accuracy. Although it has good predictive accuracy, it is slightly inferior to the method proposed in this paper, suggesting that the best combination of base models can not be attained solely based on predictive accuracy and the diversity of base models is equally important as compared to their accuracies. In summary, the MI-MDA-Stacking algorithm put forward in this study manages to strike a balance between accuracy and

Tbl. 1. Test functions.

Serial number	Design variables (D)	Test function	Range of values
TF1	10	$f(x)=\sum_{i=1}^{10}\left\{\frac{3}{10}+\sin(\frac{16}{15}x_i-1)+\left[\sin(\frac{16}{15}x_i-1)\right]^2\right\}$	$[-1,1]D$
TF2	12	$f(x)=(x_1-1)^2+\sum_{i=2}^{n}i(2x_i^2-x_{i-1})^2,\ n=12$	$[-10,10]D$
TF3	15	$f(x)=\sum_{i=1}^{14}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	$[-5,10]D$

Tbl. 2. Stacking prediction errors based on different base model selection methods.

Test function	Stacking-based model combinations	RMSE	MAE	R_Squared
TF1	A1: GBDT, LightGBM. RF, KNN	0.0442	0.0351	0.9178
	A2: GBDT, LightGBM, XGBoost	0.0447	0.0356	0.9157
	A3: RF, Ridge, KNN	0.0886	0.0727	0.6691
TF2	B1: GBDT, LightGBM, SVM	0.0362	0.0262	0.9477
	B2: LightGBM, XGBoost, SVM	0.0485	0.0357	0.9063
	B3: RF, ETR, SVM	0.0588	0.0445	0.8619
TF3	C1: GBDT, LightGBM. RF, SVM	0.0335	0.0251	0.9495
	C2: GBDT, LightGBM, SVM	0.0336	0.0258	0.9493
	C3: RF, Ridge, SVM	0.0535	0.0412	0.8713

diversity of the base models, and the selected combinations demonstrate high predictive accuracy.

COLLISION PERFORMANCE PREDICTION OF ANTI-COLLISION BEAM

Parametric Modeling of Anti-Collision Beam Structure

In this section, a parametric model of the anti-collision beam structure of an SUV is established and automatically meshed using SFE-Concept. The total number of units for the entire vehicle is 53963, as depicted in Fig. 4. The anti-collision beam model consists primarily of three components: the front anti-collision beam, crash box, and front longitudinal beam. Schematic diagrams and basic information for these key components are presented in Fig. 5 and Tbl. 3.

Building the Simplified Finite Element Model for Frontal Collision

In order to reduce the simulation calculation time, the parametric model of the anti-collision beam was integrated with the vehicle, and a simplified vehicle model was established (as shown in Fig. 6).

This study focuses solely on evaluating the performance of the anti-collision beam structure during collision. Therefore, the vehicle body is treated as a rigid body, with a total mass of 528.2 kg based on previous platform collision tests, while the mass of the anti-collision beam structure is 16.8 kg. Following the 2018 version of the C-NCAP collision test standard, we simulated a frontal collision at 50 km/h between the vehicle and a rigid wall. To analyze changes in collision force on the front longitudinal beam structure and vehicle acceleration during impact, measurement points were strategically placed within our model (refer to Fig.7 for measurement positions).

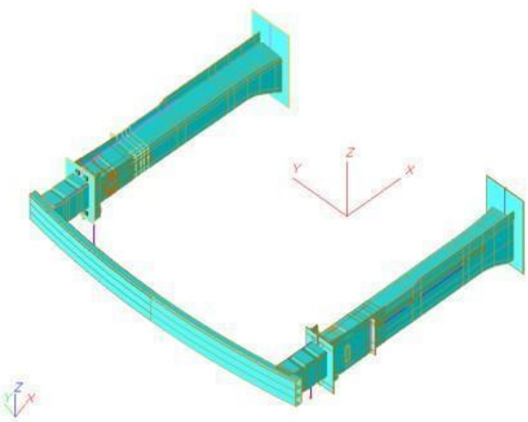

Fig. 4. Parameterized model of anti-collision beam.

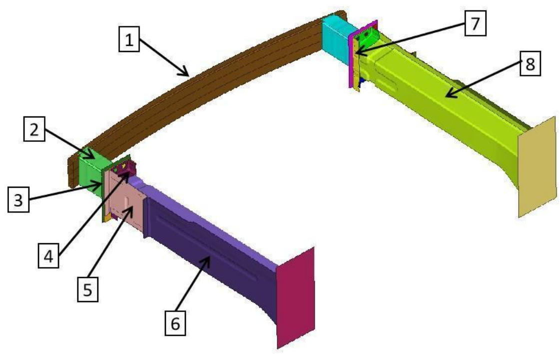

Fig. 5. Schematic diagram of anti-collision beam components.

Tbl. 3. anti-collision beam key component information.

Serial number	Part name	Material	Thickness (mm)
1	Front bumper body	AL-6060	/
2	Crash box	AL-6060	/
3	Front bumper beam connecting bracket	AL-6060	4.0
4	Crash Box Mounting Plate Bracket	DC01	2.5
5	Front longitudinal beam front outer plate	SPFC440	1.6
6	Front longitudinal beam rear section outer plate	HC340/590DP	1.8
7	Crash Box Mounting Plate	DC01	1.4
8	Front longitudinal beam inner plate	HC340/590DP	1.8

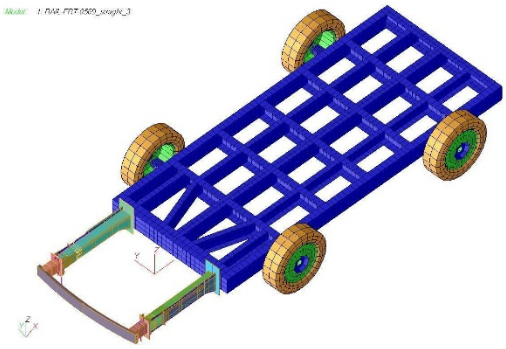

Fig. 6. Simplified model of the whole vehicle.

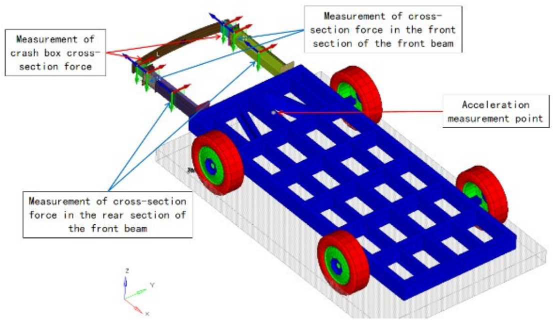

Fig. 7. Schematic of model measurement positions.

After completing the pre-processing for finite element analysis, the LS-DYNA solver is utilized to carry out the solution. LS-DYNA employs the single-point Gaussian integral method in finite element calculations, which accelerates solving speed but may result in a zero-energy mode known as the hourglass model (Li et al., 2017), characterized by deformations without strain and stress. The presence of the hourglass mode can lead to invalid results, so efforts should be made to minimize its occurrence and avoid it altogether; generally, no more than 10% of hourglass energy can be considered effective for analysis.

The energy variation curve during finite element collision simulation is depicted in Fig. 8. From this figure, it is evident that overall energy changes during the collision process adhere to conservation principles, with hourglass energy being maintained at a very low level. Therefore, it can be concluded that the results of the collision simulation are valid.

Data Access

In order to assess the collision performance of the anti-collision beam structure, it is essential to carefully select appropriate evaluation indicators. During a frontal collision, passengers in the vehicle are exposed to significant collision forces, and controlling maximum acceleration during the collision process is crucial for minimizing passenger injury. Furthermore, the maximum compression of the anti-collision beam structure during collisions can indicate its energy-absorbing capability. Therefore, maximum acceleration and maximum compression are chosen as evaluation indicators for collision performance.

Based on the structural characteristics of the anti-collision beam and engineering design experience, 13 design variables have been selected from the structural parameters of the anti-collision beam structure. The specific locations of these variables are illustrated in Fig. 9, with details provided in Tbl. 4.

To automate data acquisition, a Design of Experiments (DOE) process using the Isight software has been established. This process employs Latin hypercube sampling to select sample points within the variable range of design variables and then utilizes finite element simulation software through the Isight to automatically adjust model structural parameters and solve for corresponding collision performance at each sample point.

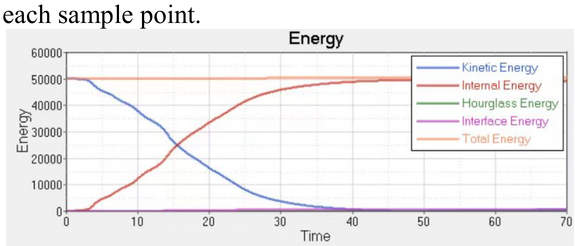

Fig. 8. Energy variation curve of the collision process.

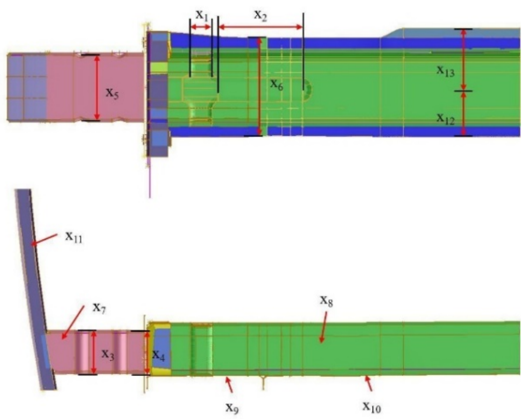

Fig. 9. Design variables' specific locations.

Construction of Collision Performance Surrogate Model

The surrogate models for maximum collision acceleration and maximum compression are developed using the MI-MDA-Stacking algorithm, establishing a mapping relationship between the structural parameters of the anti-collision beam and its collision performance. To validate the performance of the MI-MDA-Stacking algorithm, several mainstream ensemble algorithms including GBDT, LightGBM, and XGBoost are also employed to construct surrogate models.

For maximum collision acceleration, the algorithm selects ETR, Ridge, and SVM as the base model combination; for maximum compression, it selects LightGBM, ETR, Ridge, and SVM. The accuracy of these surrogate models is assessed using R-squared. The prediction results demonstrate that the surrogate models constructed by our proposed algorithm exhibit superior accuracy in predicting both maximum collision acceleration and maximum compression compared to other ensemble algorithms. Comparison with finite element simulation further confirms this high accuracy.

The comparison results show that for most sample points, the surrogate model provides predictions very close to simulation results; furthermore, it requires significantly less time than finite element simulation. Therefore, our constructed surrogate model can be utilized in optimization processes instead of finite element simulation to greatly enhance efficiency in anti-collision beam design and optimization.

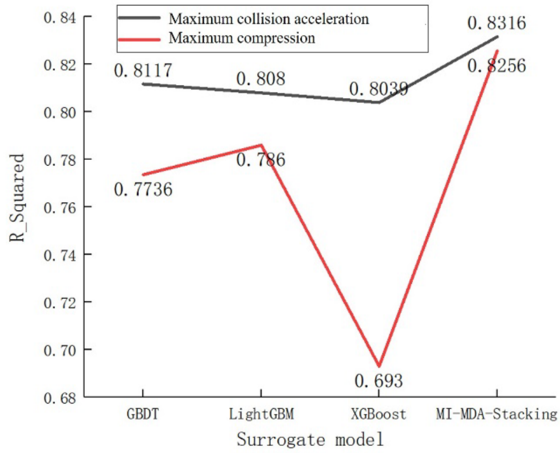

Fig. 10. Comparison of the accuracy of different ensemble surrogate models.

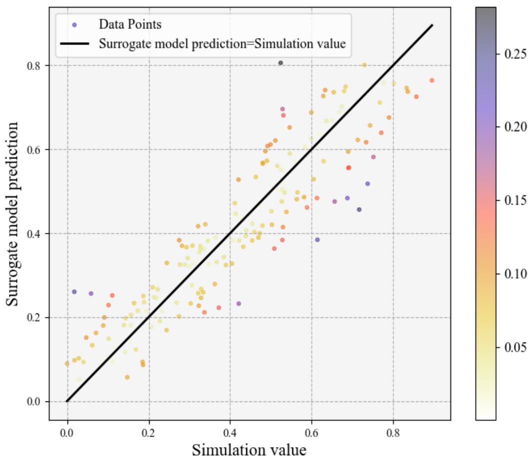

Fig. 11. Maximum collision acceleration surrogate model vs. finite element simulation results.

Tbl. 4. Design variable details.

Variable name	Variable description	Initial value (mm)	Variable range (mm)
x_1	Width of front crush groove in front longitudinal beam inner plate	35	25-45
x_2	Length of rear crush groove in front longitudinal beam inner plate	130	80-230
x_3	Rib width for energy-absorbing boxes	70	65-76
x_4	Width of energy-absorbing box	70	65-84
x_5	Height of energy-absorbing box	107	102-121
x_6	Height of the front section of the front longitudinal beam	155	150-160
x_7	Thickness of the crash box	3.0	1.5-4.5
x_8	Front longitudinal beam inner plate thickness	1.8	1.6-2.4
x_9	The thickness of the front longitudinal beam front outer plate	1.6	1.4-2.2
x_{10}	The thickness of the outer plate of the rear section of the front longitudinal beam	1.8	1.6-2.4
x_{11}	Thickness of the front bumper beam	3.0	1.5-4.5
x_{12}	Lower height of the rear section of the front longitudinal beam	85	75-95
x_{13}	Height of the upper rear section of the front longitudinal beam	85	79-105

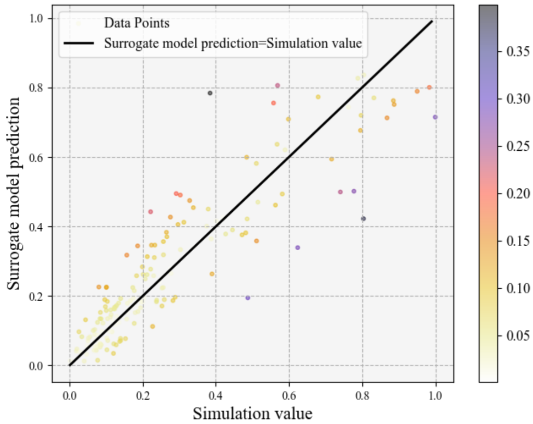

Fig. 12. Maximum compression surrogate model vs. finite element simulation results.

CONCLUSION

The process of vehicle collision is highly nonlinear, and the accuracy of traditional surrogate models becomes challenging to meet engineering design requirements as dimensionality increases. In this study, we propose a collision performance prediction method based on an enhanced stacking model for anti-collision beam structures. This method comprehensively considers the accuracy and relevance of each base model and implements adaptive selection strategies to improve the prediction accuracy of the stacking model. Through validation in three test functions, our proposed improved stacking model demonstrates superior prediction performance. Furthermore, we utilize this algorithm to construct surrogate models for maximum collision acceleration and maximum compression during the collision process. Comparison with simulation results reveals that the constructed surrogate models provide predictions close to simulation values and can effectively replace finite element analysis. Additionally, our method significantly reduces prediction computation time compared to finite element simulation time. Experimental results validate the feasibility and effectiveness of our proposed collision performance prediction method for anti-collision beam structures.

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基於 MI-MDA-Stacking 算法的防撞梁碰撞性能預測

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摘 要

為節省傳統防撞梁設計過程中有限元分析耗費的計算資源與人力成本，構建車輛碰撞代理模型以預測碰撞性能已成為一種高效且可行的方法。為提升代理模型預測精度，提出了一種基於互資訊理論和隨機森林的 Stacking 算法基模型選擇策略，並構建了防撞梁結構在碰撞過程中最大碰撞加速度和最大壓縮量的高精度代理模型。首先，介紹了互資訊與隨機森林的基本原理，並提出了演算法框架。其次，利用數學測試函數驗證了演算法的有效性。最終，利用提出的演算法構建高精度代理模型從而預測防撞梁碰撞性能，結果表明構建的代理模型能夠快速、準確地預測防撞梁碰撞性能。本研究對汽車結構安全性設計具有重要的工程意義。