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Research Article

Evaluation of the Risk of Truck Platoon under Crosswind regarding the Lateral Displacement on Horizontal Curves

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Driving safety on horizontal curves under crosswinds has always been a concern for researchers. However, previous studies focused on single vehicles, especially single trucks. The safety of the truck platoon under crosswinds on horizontal curves was rarely examined. To fill such a gap, this study establishes a model for evaluating the safety of truck platoons under crosswinds on curves. After obtaining aerodynamic coefficients, a cosimulation model of a three-truck platoon is established with Trucksim and Simulink. The influencing factors on the lateral displacement of the truck platoon were analyzed, and the safety of the truck platoon under crosswinds on horizontal curves was then quantified with the response surface method. The results show that the fully autonomous platoon is safer than the human-led platoon. In a three-vehicle platoon, the smaller the lateral displacement of the truck, the further back the truck, and the lateral displacement of the vehicle increases with the loading of the truck. The safety index is computed to quantify the reliability of the truck platoon. The results indicate that the safety index increases with a decrease in the mean wind velocity and mean vehicle velocity and increases with an increase in the mean radius. When crosswinds come from the inside of the curve, the safety index increases with an increase in the mean superelevation; for crosswinds from the outside of the curve, the safety index rises with the drop of superelevation. The proposed approach can quantify the safety level of truck platoons under crosswinds on horizontal curves, and the results provide guidance to support the decision-making of transportation management agencies.

1. Introduction

Driving safety on horizontal curves under crosswinds has always been a research focus. Horizontal curves are relatively dangerous segments due to the centripetal force exerted on the vehicle driving on curves, leading to excess lateral displacement that can cause accidents [1]. Previous studies have shown that design features, including curve radius, superelevation, curve length, and roadside conditions, are found to significantly affect accidents [2, 3]. The highway safety manual provides safety performance models with different curve features. Still, other studies focused on methods of horizontal curve safety using factors such as high-friction surface treatments [4] and spatial considerations [5]. However, road surface conditions and geometric features are still the main factors concerning the safety of vehicles under hazardous driving conditions [6].

As compared to passenger cars, the safety of high-sided vehicles on curves is of particular interest, especially under crosswinds. Baker [7, 8] defined the accidents of high-sided vehicles in windy environments into three types: sideslip, rollover, and rotational accidents. He carried out a series of research with rigid vehicle simulation models to investigate the risk of vehicle accidents and identified contributing factors that had the greatest effect on the probability of wind-induced accidents. To evaluate the safety performance under various conditions more accurately and comprehensively, reliability models based on the kinetic simulation models are widely used. Snæbjörnsson et al. [9] developed a general probability model and applied it to assess the reliability of road vehicles in harsh environments, analyzing the effects of wind direction, wind velocity, road friction coefficient, and superelevation. Chen et al. [10] developed a framework based on a transient dynamic vehicle simulation model to consider the relationship between vehicles and harsh driving conditions such as wind gusts, ice, and curves. Shin and Lee [11] evaluated the probability of vehicle overturning and sideslip accidents in windy environments considering vehicle speed, tire-road friction coefficient, superelevation, wind speed factors, etc., with design optimization of road radius to improve vehicle safety. These results based on traditional heavy trucks focused on the rollover and sideslip accident, but they overlooked another type of wind-induced accident, an incursion into adjacent lanes due to wind-induced excessive lateral displacement, which can occur, before the criterion for a rollover accident or sideslip accident is met. The incursion into adjacent lanes can pose severe threats to safety at wind-prone spots, like long-span bridges and tunnel portals.

The abovementioned studies focused only on single trucks, while studies on the driving safety of truck platoons under crosswinds on horizontal curves are still lacking. Given the booming development of connected and automated vehicle (CAV) technologies, truck platooning becomes the focus not only for researchers but also for transportation industries. It is important to guarantee the safe operation of truck platoons before their large-scale deployment. Nevertheless, driving safety of truck platoons in harsh conditions, such as on curves under crosswinds, has been largely ignored. Safety studies on platoon vehicles are relatively well conducted for string stability, realistic scenarios [12], and technical failures [13]. Axelsson [14] provided an overview of the safety of vehicles in platoons, outlining fault types and ways to improve safety performance. Most of the research focuses on longitudinal safety [15], and another important aspect of safety is the lateral safety of truck platoons, which is rarely concerned. When trucks travel in a platoon, the shortening of the spacing distance leads to changes in the aerodynamic coefficients of vehicles, making truck platoons respond differently from individual trucks under crosswind, and the characteristics of multivehicle platoon operation make the impact of incursion accidents on surrounding vehicles more serious. Ma et al. [15] studied the lateral displacement of autonomous truck platoons and proposed a reliability-based safety assessment method to quantify the risks of the truck platoon. However, their study focused on the straight segment and ignored the impact of horizontal alignment.

Meanwhile, the impact of driving performance on lateral displacements of trucks under crosswinds cannot be ignored for human-driven and autonomous trucks. As many control algorithms of autonomous trucks also simulated the behaviors of human drivers, previous studies on driver behavior still shed light on autonomous vehicles. Baker [16] proposed a model to describe drivers' steering behavior under the influence of crosswinds by considering drivers' reaction time and driver characteristics. Based on Baker's model, Chen and Cai [17] used the front wheel steering angle instead of the steering angle at the vehicle's center of gravity, which better captured drivers' steering behavior. Chen et al. [18] later conducted a driving simulation study under crosswind using a high fidelity driving simulator and proposed a method to evaluate the driver's ability to cope with the crosswind. The drivers' reaction time has been a key indicator of the abovementioned studies. The importance of drivers' reaction time applies to truck platoons as well, since both human-led truck platoons and fully autonomous truck platoons are both being tested. Although the driving performance of the human-driven vehicle was extensively examined, the differences between the safety of human-led and autonomous truck platoons under crosswinds are rarely examined, which is worth exploring in the era of mixed traffic of autonomous vehicles and manned vehicles.

Based on the above discussion, the current study aims to fill those identified research gaps in the existing literature. Specifically, the present study proposes a reliability-based method to quantify the safety of truck platoons on horizontal curves under crosswinds. In addition, the impact of reaction time and the loading strategy of the truck platoon are also investigated. Driving safety in extreme conditions has been an ongoing issue that has prevented autonomous vehicles from moving to L4 or higher levels of automation. The current study potentially contributes to the state of the art in that regard. The results can support the decision-making of traffic management considering platoon operation in harsh conditions.

The rest of the paper is organized as follows: Section 2 presents the four main steps of the framework proposed. Section 3 displays the results and discussion. Section 4 concludes the main findings of the paper.

2. Methods

2.1. Aerodynamic Characteristics of Truck Platoons. When trucks are traveling in platoons, their aerodynamic responses differ from that of a single truck due to shortened vehicle spacing. To accurately simulate the truck platoon's response under crosswinds, the relationship between aerodynamics and slip angles should be developed. In this study, computational fluid dynamic (CFD) simulations are conducted to obtain the aerodynamic features of the three-truck platoon, where a typical Scania truck model is adopted. For details of the setting of the CFD simulation, readers are referred to a previous study [15], where various simulation scenarios for a three-truck platoon were carried out and validated.

Figure 1 presents the aerodynamics of the truck platoon when intervehicle spacing between trucks is half the truck length. It shows that the drag coefficients of a single truck are significantly different from those of platoon vehicles. There is also a significant difference between the leading truck, the middle one, and the trailing one within the platoon. The

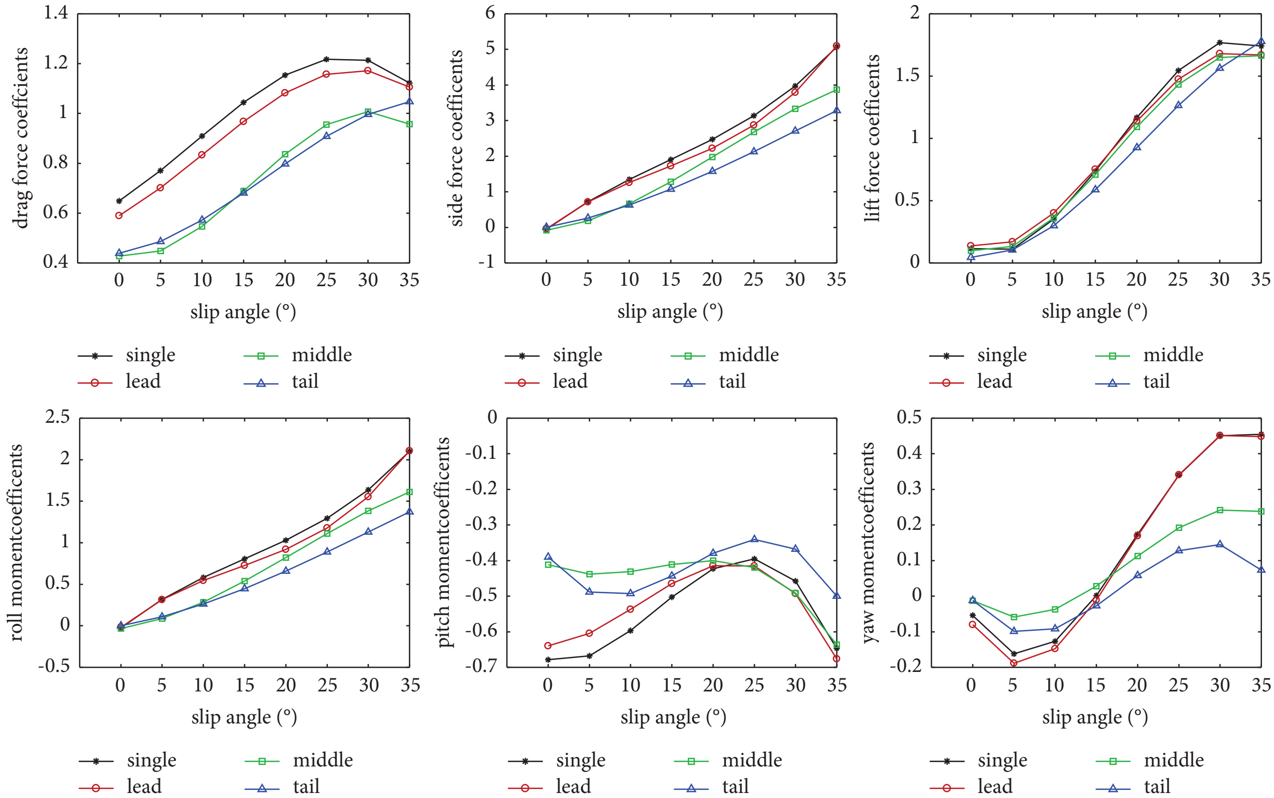

Figure 1: Simulation results of aerodynamic coefficients for truck platoons.

aerodynamic coefficient of the lead vehicle is the largest within the truck platoon, while it is still smaller than that of the single truck. The difference in aerodynamic coefficients indicates that the responses of trucks within a platoon also differ accordingly under crosswinds compared to those of a single truck.

Truck spacing (measured as vehicle length L, $L = 16.5$ m) equal to 0.5 L with a range of sideslip angles between 0° and 35° in increments of 5° was tested in CFD simulations. A similar virtual wind tunnel is set up, and a calculation domain is used. As a result, the aerodynamic coefficients used in this paper were obtained.

2.2. Contributing Factors. While differences in aerodynamic coefficients significantly affect the motion of platoon vehicles, factors with impacts on single vehicles have effects on platoons as well. Except for crosswinds that have a significant impact on lateral displacements of vehicles, rain and snow on the road may reduce the friction coefficient [19] between tires and the road surface, which in turn reduces friction and increases the lateral displacement of curves. Thus, the wind heading, wind velocity, and friction coefficient are taken as contributing factors to the safety of the truck platoon.

Apart from environmental factors, the characteristics of the truck platoon will undoubtedly affect its motion under crosswinds. As the velocity of the truck directly affects the result of lateral displacements, vehicle velocity is considered a contributing factor to the safety of the truck platoon. The size of the truck unit, spacing distance, load, and position in a platoon also affect the results, as the aerodynamic drag coefficient of the rear vehicle can be greatly reduced after entering the wake area of the front vehicle [20]. When the vehicle is fully loaded, half-loaded, and empty in the leading, middle, and trailing position, the differences in the vehicle's center of gravity height and position within a platoon also have a significant impact on the results of lateral displacement, so the impact of the formation strategy on the truck platoon's response is considered. As the motion results are determined by the truck's control model as well, the current study focuses on the influence of reaction time, the key parameter of the control model, to explore the differences in lateral displacements between a human-driven truck and an autonomous truck.

As the magnitude of superelevation and radius have an impact on the force in the lateral direction of the vehicle force analysis, the road alignment design factors of a horizontal curve are very important for the safety of the vehicle. Therefore, superelevation and radius are taken as contributing factors to the safety of the truck platoon.

2.3. Truck Platoon Simulation. The impact of the selected safety elements needs to be explored based on the simulation program. The simulation model used in the current study is built based on the cosimulation of Trucksim and Simulink. In Trucksim software, the vehicle model, lateral control model, and road model can be set and the wind speed and direction can be adjusted. Simulink can realize the platoon control of trucks.

Table 1: Truck model geometry.

Item		Tractor	Semitrailer
Length (mm)		2000	8000
Height (mm)		4000	2600
Width (mm)		2500	3000
Wheelbase (mm)	Axle 2	3500	6700
	Axle 3	4770	7900
Center of mass height (mm)		1175	1936
Spring mass (kg)		4455	5500
Rotational inertia pitch inertia	Pitch inertia (kg/m^2)	2283.9	8997.1
	Sway inertia (kg/m^2)	35402.8	150000
	Transverse inertia (kg/m^2)	34802.6	150000
Turning radius	X-axis (m)	0.716	1.279
	Y-axis (m)	2.819	5.222
	Y-axis (m)	2.795	5.222

The speed and direction of the crosswind will have an impact on the operation status of the vehicle; therefore, its time-varying relationship needs to be considered. The velocity of the crosswind is set to increase linearly from 5 s to 7 s, reaching its peak of 40 km/h, stay stable for 3 seconds, and then drop to 0 at 12 s.

2.3.1. Truck Model. Trucks with semitrailers are widely used in cargo transportation, but they are a prominent hazard source, thus becoming one of the most concerning research topics among many trucks. The center of gravity of the semitrailer is located high, contributing to the poor stability of trucks; thus, the proportion of accidents related to lateral instability is higher in semitrailers. Three homogeneous semitrailers make up the truck platoon model used in this paper, and the selected truck model is consistent with the truck model used in the CFD simulation [15], which is a Scania truck commonly found in China. The relevant parameter settings for the truck models are shown in Table 1.

2.3.2. Platooning Algorithms. Commonly used longitudinal control methods when truck platoons are in automatic operation mode include adaptive cruise control (ACC), cooperative adaptive cruise control (CACC), and cooperative look-ahead control (CLAC). The ACC mode is adopted in the simulation of the middle truck and tail truck in the platoon, which has a clear logic and has been widely used to control the speed of platoon vehicles. If the distance is less than the threshold, the throttle is closed and the brake is applied. The lead truck is set to be manually driven in the current study, as the complex driving condition has blocked the use of full self-driving on open roads in practice.

Lateral control methods for autonomous trucks have undergone a certain development process. Current methods applied to vehicle lateral control include [21] proportional-integral-differential (PID) control methods, linear quadratic regulator (LQR), optimal preview control (OPC), and model predictive control (MPC) methods. In addition, robust control, adaptive control, sliding mode control, and fuzzy control methods are also commonly used. Optimal control has a good tracking effect and has become the main method for landing applications, and the lateral control model in this study is accomplished by Macdam's [22] optimal preview control model. The model has a clear physical meaning and a simple structure, and it has been used in numerous studies and products based on Trucksim. Different reaction time values can be set to simulate the difference between human driver and autonomous vehicle reaction characteristics considering safety influences.

2.4. Reliability-Based Assessment Model. Based on the simulation model above, a reliability-based model can be set up to measure the safety level of truck platoons. The safety index of platoon vehicles can be given, with the uncertainties of influencing factors taken into consideration.

2.4.1. Limit State Function. The current study focused on the incursion into the neighboring lane; thus, the limit state of the safety performance under crosswinds can be defined as the lateral displacement equaling the maximum allowable threshold. Baker [7]considered lateral displacements beyond 0.5 m as unsafe domains. This result has been followed by researchers in this field. Therefore, the safety performance function is set as

$$f(X) = 0.5 - \text{lat\_vehicle}. \quad (1)$$

Since the safety performance of the three-truck platoon is a tandem relationship, an accident of one truck is considered an accident of the platoon, and thus, the limit state is set as the maximum value of the lateral displacement of the three trucks in the truck platoon. If the lateral displacement of one or more trucks exceeds 0.5 m, it is considered to have invaded adjacent lanes and entered the dangerous domain. Considering the width of a lane, the lateral displacement after the vehicle has already invaded the adjacent lane is meaningless, so the cases that exceed this upper bound value are processed in the data preprocessing stage.

Table 2: Basic random variables.

Variables	Notation	Distribution	Standard deviation	Source
Road friction coefficient	μ_f	Truncated normal	0.05	Snæbjörnsson et al. [9]
Wind heading (km/h)	φ	Normal	$0.15\mu_{\varphi}$	Snæbjörnsson et al. [9]
Wind speed (km/h)	U	Normal	7.2	Snæbjörnsson et al. [9]
Driving speed (km/h)	V	Normal	$0.15\mu_V$	Snæbjörnsson et al. [9]
Radius	R	Normal	$0.1\mu_R$	Assumed
Superelevation	i	Normal	$0.1\mu_i$	Shin and Lee [19]

2.4.2. Basic Random Selection. Considering the magnitude of the effects on the safety of vehicle operation under the effect of crosswinds, wind velocity, wind direction, road friction coefficients, radius, superelevation, and vehicle speed are selected as the influencing factors for the study. Combined with the existing studies, appropriate variance and mean values are set, as shown in Table 2.

2.4.3. Gaussian Process Regression-Based Response Surface Method. Common response surface methods for taking sample points include the Box–Behnken design (BBD) method and the central composite design (CCD) method [23], both of which aim to select $2n+1$ points to meet the requirements of the fitting response surface. Since the CCD method involves operating conditions that would exceed the experimental safety threshold, the BBD method is used to take sample points. The sample points obtained from the BBD experiments and the sample points in experiments only considering single factors were all used to develop the response surface model. The classical response surface-fitting method uses a quadratic polynomial without cross terms as a performance function [24]. However, the accuracy of this method is not high enough, especially when it is impossible to iterate sample points for experiments. With the development of machine-learning methods and the improvement of computational ability, researchers have introduced artificial neural networks [25] (ANNs), radial basis functions (RBFs), and support vector machines (SVMs). Neural network regression models have better regression capabilities than classical RSM models but are less effective in solving small sample problems [25, 26]. SVM is effective in the small sample case [26], but its effectiveness is strongly influenced by the choice of the kernel function. Su [27] et al. introduced Gaussian process regression (GPR) into the fitting of performance functions and achieved good results. As a probabilistic model suitable for small sample regression, its independent variables are all set as random variables and have good interpretability and practicality [27]. Therefore, GPR is adopted as the response surface method and compared with SVM and the classical response surface model. The compared metrics are the mean absolute error (MAE) and root mean squared error (RMSE):

$$\begin{aligned} \mathrm{MAE} &= \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - Y_i^*\right|, \\ \mathrm{RMSE} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_i^*\right)^2}, \end{aligned} \tag{2}$$

where Y_i is the true value and Y_i^* is the estimated value.

It is assumed that all statistical characteristics of GPR are fully specified by the mean and covariance functions. The joint Gaussian prior distribution of m training samples and one output sample is

$$\begin{bmatrix} y \\ y^* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X,X) + \sigma_n{}^2 I & K(X,x^*) \\ K(X,x^*)^T & k(x^*,x^*) \end{bmatrix}\right), \tag{3}$$

where $K(X,x^*)$ is an $m\times m$ symmetric positive definite covariance matrix with any element K_{ij} of the matrix measuring the correlation between x_i and x_j $(i, j = 1, 2\cdots m)$, $K(X,x^*)$ is an $m\times 1$ covariance matrix generated from all the input training samples x of the input test samples X, and $k(x^*,x^*)$ is the covariance matrix x^* of itself. The covariance function $k_y(x_i,x_j)$ is the kernel of the Gaussian process regression. The optimal hyperparameters of the model can be obtained by the maximum likelihood method. The predicted posterior distribution can be obtained by

$$y^* \sim N\left(\overline{y}^*(x^*), \sigma(x^*)\right). \tag{4}$$

2.4.4. Safety Index. A typical first-order reliability method is chosen to calculate the safety index. Defined as the vector consisting of standard deviations of the variables, the safety index at the point of the mean can be expressed as [9]

$$\beta = \frac{g(x)}{\left[\nabla g(x)^T C_x \nabla g(x)\right]^{1/2}}. \tag{5}$$

The relationship between the probability of failure and the safety index can be approximated by the following equation [28]:

$$P_{\text{failure}} = \Phi(-\beta), \tag{6}$$

where Φ is the standard normal probability distribution function. A positive value of the safety index corresponds to a failure probability between 0 and 0.5, while a negative value of the safety index corresponds to a failure probability between 0.5 and 1.

3. Results and Discussion

3.1. The Impact of the Reaction Time. The characteristics of the truck platoon include the driver reaction time, vehicle speed, vehicle spacing, and vehicle load of the lateral control model. Manually driven trucks and autonomous trucks react differently under crosswinds due to differences in their reaction time; thus, steering wheel angles generated by the control model used are delayed by the amount of time on the x-axis to simulate the neuromuscular delay in human drivers.

Figure 2 shows the relationship between the reaction time and the maximum lateral displacement of the truck platoon when the vehicle speed is set as 70 km/h and wind speed is set as 40 km/h. It can be observed in Figure 2 that the maximum lateral displacement in the case of the reaction time corresponding to the autonomous truck (below 0.1 s [29]) is significantly smaller than the maximum lateral displacement in the case of the reaction time of the manually driven truck (0.2 s–0.3 s [29]), and the maximum lateral displacement of three platoon vehicles gradually increases as the reaction time increases, reflecting the better safety of the autonomous trucks.

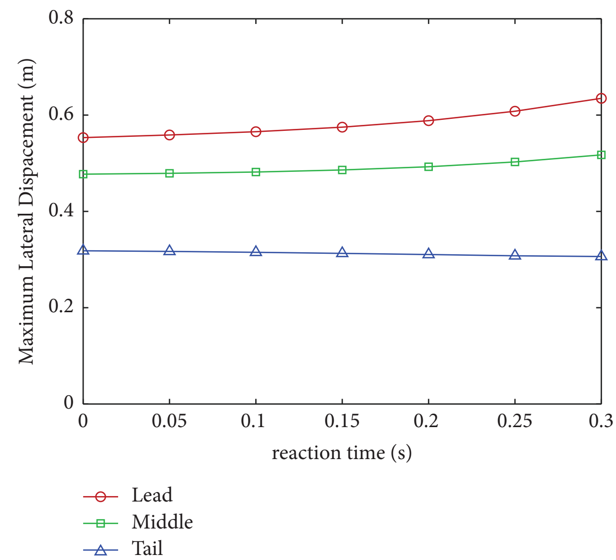

Figure 2: Maximum lateral offset at different reactions.

3.2. The Impact of the Formation Strategy on the Truck Platoon's Response. The response of trucks is affected not only by the driver reaction time but also by the formation strategy. Characteristics of trucks with different loading vary significantly in different positions within a platoon, which affects the results of the lateral displacement. From Figure 3, it can be seen that the maximum lateral displacement of platoon vehicles is the largest when the load is concentrated on the lead truck. When the load is concentrated on the tail truck, the maximum lateral displacement of platoon vehicles is the smallest. When both the middle and tail trucks are fully loaded with an empty lead truck, the platoon experiences the smallest lateral displacement.

Furthermore, Figure 3 shows that the lateral displacement of a truck within a platoon increases with loading. Moreover, the further back a truck is in the platoon, the smaller the maximum lateral displacement when all trucks have the same loads. The order of trucks with different loading influences the maximum lateral displacement of the platoon. These findings can be useful to guide the formation strategy of the truck platoon with different loading situations when reorganizing the platoon. When reorganizing the platoon, vehicles with more cargo should be arranged at the rear of the platoon, and loaded trucks should avoid the lead truck position to minimize the maximum lateral displacement of trucks in the platoon.

3.3. Comparison of Response Surface Models. The choice of the kernel has a significant effect on the fitting results of the response surface. Three kernels are used for comparison in the current research. The squared exponential kernel is of the same form as the RBF kernel, and its hyperparameters are length scale parameters l:

$$k\left(x_i, x_j\right) = \exp\left(-\frac{1}{2l^2}\left\|x_i - x_j\right\|^2\right). \tag{7}$$

The rational quadratic kernel can be viewed as a mixture of RBF kernels with different characteristic length scales, where the scale mixing parameter a is a scalar and must be positive. The kernel is of the form:

$$k\left(x_i, x_j\right) = \left(1 + \frac{\left\|x_i, x_j\right\|^2}{2al^2}\right)^{-a}. \tag{8}$$

The Matern kernel is a generalization of the squared exponential kernel:

$$k\left(x_i, x_j\right) = \frac{2^{1-\nu}}{\Gamma(\nu)}\left(\sqrt{2\nu}\ \frac{\left\|x_i - x_j\right\|}{\rho}\right)^{\nu} K_\nu\left(\sqrt{2\nu}\ \frac{\left\|x_i - x_j\right\|}{\rho}\right)^{\nu}, \tag{9}$$

where Γ is the gamma function, K_ν is the modified Bessel function, and ρ and ν are the positive parameter of the covariance. The parameter ν controls the smoothness of the learning function, and the Matern kernel of size $\nu = 2.5$ is used in this paper. All regression models based on machine-learning methods are conducted ten-fold cross-validation to evaluate their generalizability.

The comparison reveals that the RMSE and MAE of GPR with the Matern kernel are optimal as shown in Table 3. Therefore, the GPR function paired with the Matern kernel was chosen as the regression model for fitting the response surface in this paper.

3.4. Reliability Analysis. Once the response surface model is determined, it is possible to assess the probability of a lateral accident in a truck platoon. When the safety index is equal to 0, it means that the probability of an accident is 0.5 [28]. The larger the safety index is, the safer the truck platoon is under crosswinds. The mean road friction coefficient of the road is set as 0.6, which corresponds to a dry road condition. Since it obeys a truncated normal distribution, it is transformed into a normal distribution with the method proposed by the Joint Committee on Structural Safety, and the transformed mean value is 0.5 with a mean wind direction of 70°.

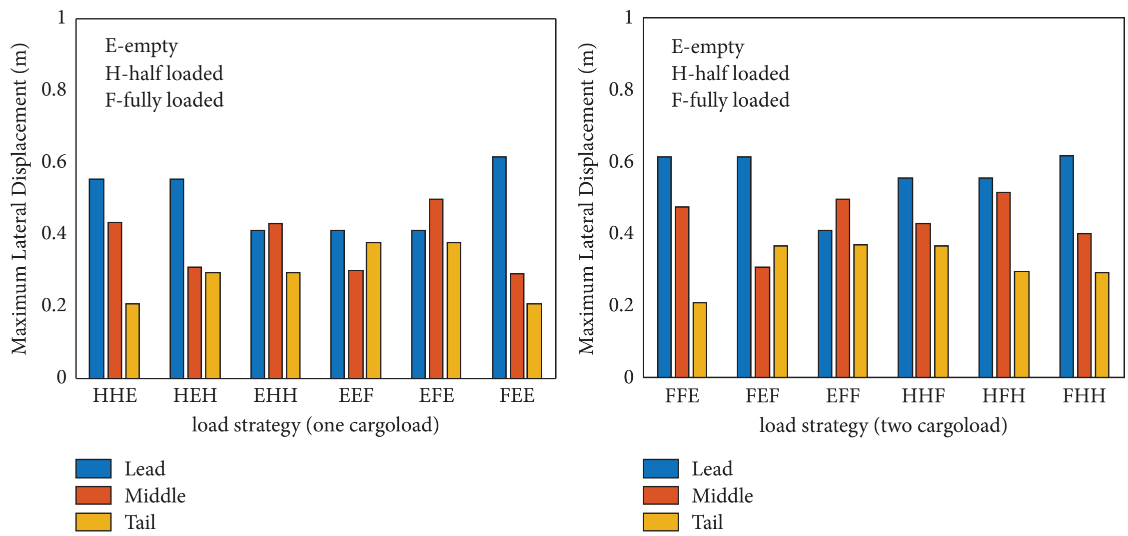

Figure 3: Maximum lateral offset at different loading.

Table 3: Results of ten-fold cross-validation.

Models	MAE	RMSE
Pure quadratic polynomial	0.1860	0.2699
Linear kernel SVM	0.2127	0.4045
RBF kernel SVM	0.2045	0.3670
Matern kernel GPR	0.0945	0.1462
Square exponential kernel GPR	0.1084	0.1547
Rational quadratic kernel GPR	0.1025	0.1504

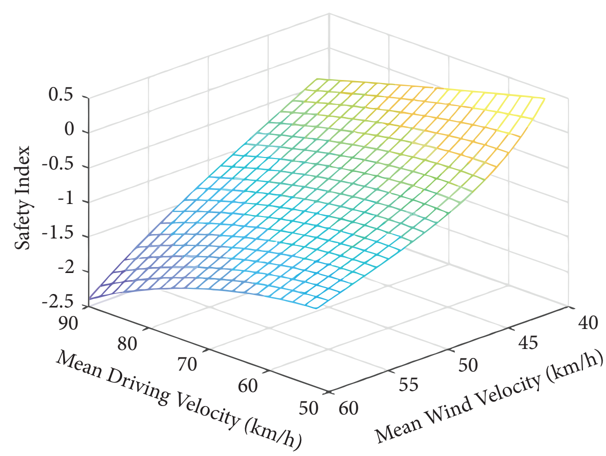

Figure 4: Safety index as a function of the mean wind velocity and mean vehicle velocity.

The mean radius of the curve is set as 400 m, and the mean superelevation is set as 3%. As Figure 4 shows, the safety index usually increases with a decrease in the mean wind velocity and the mean vehicle velocity. The safety index increases where the mean vehicle velocity and mean wind velocity both decrease, which confirms the reasonableness of the speed limit. The effect of the road friction coefficient on truck lateral safety has been studied, so the current study focuses on the effect of radius and superelevation and combines it with wind velocity to facilitate the set of reasonable management measures according to the actual and forecast wind level. The effect of these two geometric features is also explored combined with vehicle speed to provide the basis for setting speed limits.

The results of fitting the safety index as a function of the mean wind velocity and the mean radius at the mean vehicle velocity of 70 km/h and the mean superelevation of 3% are shown in Figure 5. With an increase in wind velocity and decrease in radius, the safety index gradually decreases. When the radius is less than 500 m, the safety index decreases rapidly with an increase in wind velocity; thus, truck platoons have a higher risk level on curves with a radius of less than 500 m. When the mean wind velocity is 60 km/h, the safety index is fitted as a function of the mean radius and mean as shown in Figure 6; at this time, no matter how the platoon speed changes, the safety index is less than 0, which indicates that the risk of wind-caused accidents of the truck platoon is higher than 0.5 in this case.

Curves with small radii are usually paired with superelevation, which can have an impact on the lateral stability of the vehicle. Therefore, the relationship between the safety index and the mean superelevation is also worth studying. There is a significant difference in the safety index law of the vehicle between the conditions when the wind comes from the inside and the outside of the curve; thus, the two situations are discussed separately. The directions of winds from the inside and outside of the curves, namely, “inside wind” and “outside wind,” is illustrated in Figure 7. The mean vehicle velocity is set as 70 km/h, and the mean radius is set as 300 m; the results of fitting the safety index as a function of the mean wind velocity and the mean superelevation of winds from the inside of the curve are shown in Figure 8. With a gradual increase in superelevation, the safety index increases due to the crosswind from the inside of the curve, as extra centripetal force is needed from superelevation to compensate for the effects of the crosswind. As

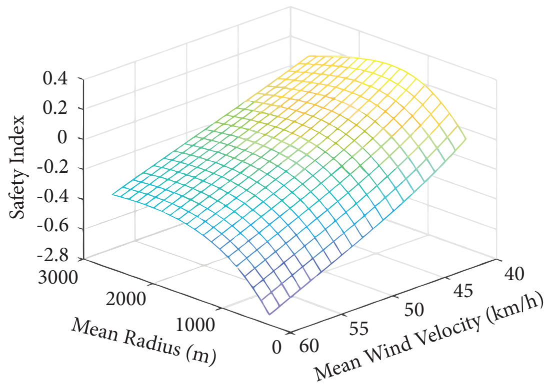

Figure 5: Safety index as a function of the mean wind velocity and mean radius.

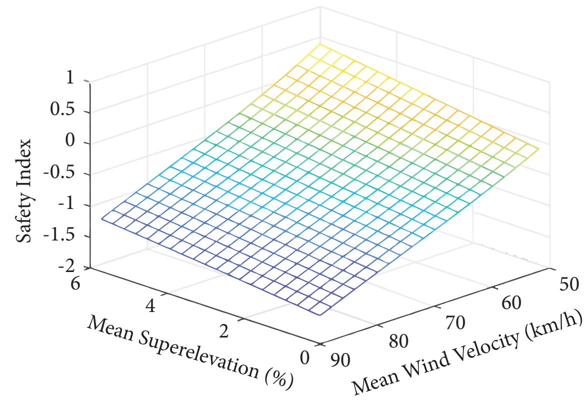

Figure 8: Safety index as a function of the mean wind velocity and mean superelevation (inside wind).

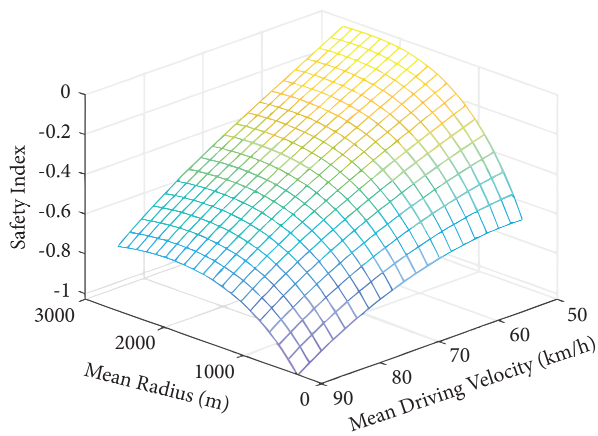

Figure 6: Safety index as a function of the mean vehicle velocity and mean radius.

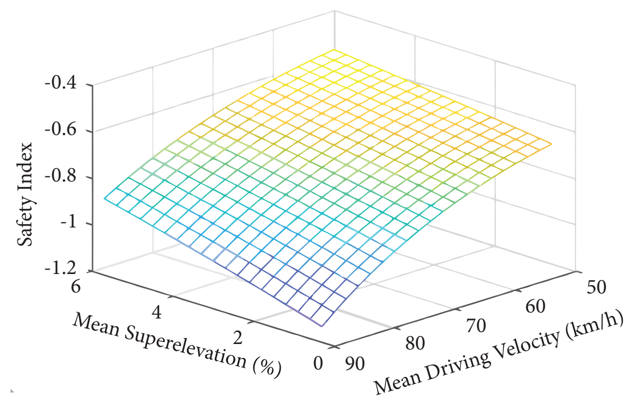

Figure 9: Safety index as a function of the mean vehicle velocity and mean superelevation (inside wind).

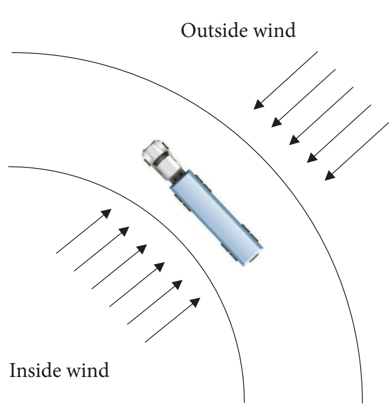

Figure 7: The directions of the winds from inside and outside of the curve.

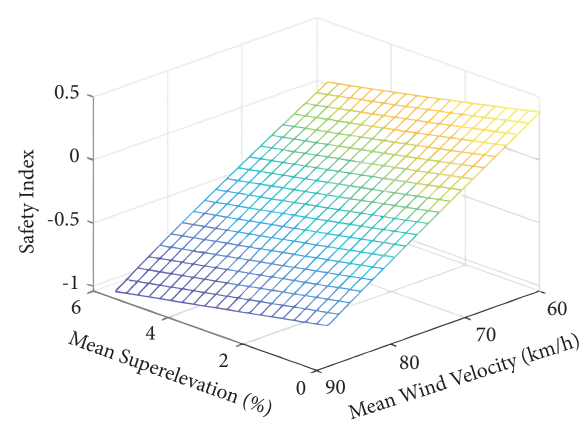

Figure 10: Safety index as a function of the mean wind velocity and mean superelevation (outside wind).

the wind speed increases, the safety index decreases. Similarly, the results of fitting the safety index with the mean velocity and the mean superelevation are shown in Figure 9, where the mean wind velocity is still fixed at 60 km/h.

Under crosswind from the outside of the curves, the safety index drops with an increase in superelevation, as shown in Figures 10 and 11, because the crosswind can counteract the centrifugal force of the vehicle running on the curve; thus, too large superelevation will only weaken the lateral safety of the vehicle and cause a larger lateral displacement. The above results show that there is a significant difference in the safety index rule of the vehicle when the wind comes from the inside and the outside of the curve. When calculating reliability, we should not only

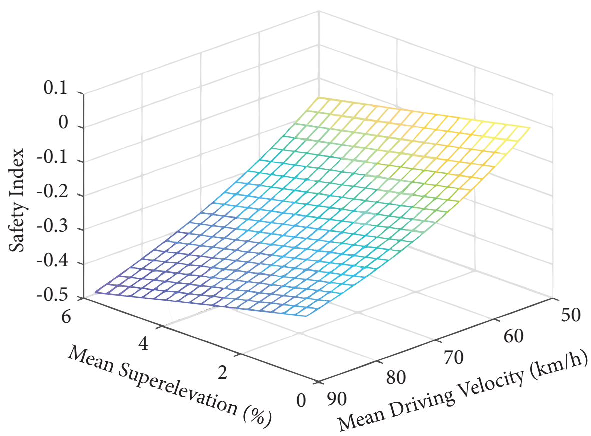

Figure 11: Safety index as a function of the mean vehicle velocity and mean superelevation (outside wind).

focus on the magnitude of wind velocity but also distinguish whether the wind comes from the inside or outside of the curve.

4. Conclusions

Based on reliability theory, a method for evaluating the safety of truck platoons on curved sections of highways under crosswinds is established. The proposed method includes three main steps. First, based on the aerodynamic simulation results of the truck platoon, the truck platoon model is built based on the joint simulation of Trucksim and Simulink. The influencing factors of safety are then analyzed. Finally, the response surface model is established, and the safety index is calculated by Gaussian process regression; the reliability of the truck platoon on the curved section of highway under crosswinds is analyzed considering the effects of different factors based on the safety index. The main research findings are summarized as follows:

(1) The results show that the maximum lateral displacement of the truck platoon gradually increases with an increase in the reaction time, reflecting the lower safety of manually driven trucks. At the same time, truck position and truck loading also significantly affect the lateral safety of the platoon. In a three-vehicle platoon, the further back the truck is, the smaller the lateral displacement is; the lateral displacement of the vehicle is the largest when the truck is fully loaded and the smallest when it is empty. This conclusion can be used to guide the cargo loading and the positioning strategy of trucks when reorganizing the platoon.

(2) A response surface based on Gaussian process regression was established, and the reliability of lateral deviation accidents of truck platoons operating in curved sections of highways was assessed by safety indices. The evaluation results show that the safety index usually increases with the fall in the mean wind velocity and increases with the drop in the mean vehicle velocity. This result can provide a quantitative basis for traffic management.

(3) The curve radius and superelevation of the highway significantly affect the lateral safety of truck platoons. With a decrease in the average radius, the safety index gradually decreases. When the radius is less than 500 m, the safety index decreases rapidly with an increase in wind velocity. If the wind comes from the inside of the curve, the safety index increases with an increase in superelevation, and if the wind comes from the outer side, the safety index decreases with an increase in superelevation. Therefore, attention should be paid to differentiating the wind direction to give the reliability index.

In summary, the reliability-based approach proposed in this paper quantifies the safety level of truck platoons on curved sections of highways under crosswinds. The results of the study are as expected, and the given assessment method is easy to operate, which provides a quantitative basis for ensuring the safety of truck platoons on mountainous highways.

There are still some limitations in this study: (1) The effect of vertical curves on safety has not been considered in this study because the braking performance of platoon vehicles was not considered. (2) Multiple simulations are used for analysis, while there is still a lack of validation based on actual measurement data. (3) Only ACC-based platoon control and optimal preview lateral control are implemented, and more advanced longitudinal and lateral control algorithms have not been considered.

Data Availability

The CFD simulation data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Wentao Wu was responsible for methodology, investigation, writing the original draft, writing, reviewing, and editing, and visualization. Xiaoxiang Ma was responsible for conceptualization, methodology, writing the original draft, writing, reviewing, and editing, and supervision.

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