CFRLI-IDM: A Counterfactual Risk Level Inference Based Intelligence Driver Model for Extremely Aggressive Cut-in Scenario in China

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Abstract: When conducting unmanned delivery tasks on side roads in China, unmanned delivery vehicles sometimes face a dual challenge of aggressive cut-ins and reckless followers driving closely behind them. To address this challenge, we propose a cut-in response strategy named Counterfactual Risk Level Inference-based Intelligence Driver Model (CFRLI-IDM). The CFRLI-IDM method utilizes an improved Intelligent Driver Model (IDM) as the initial longitudinal control strategy for the ego vehicle. It then leverages counterfactual inference to construct an optimization problem, aiming to derive a longitudinal control strategy that satisfies the ego vehicle's risk threshold constraint while maximizing compliance with the rear vehicle's maximum acceptable braking deceleration constraint, with minimal changes to the initial strategy. To evaluate the effectiveness of our proposed method, we design an extremely challenging cut-in simulation scenario incorporating the aforementioned factors and validate the algorithm within this simulated environment. Experimental results demonstrate that our method prioritizes the safety of the ego vehicle while ensuring the safety of the rear vehicle as much as possible, substantially reducing the likelihood of safety accidents occurring in such complex scenarios.

1 INTRODUCTION

The development of e-commerce has provided vast opportunities space for China's unmanned delivery business, while also posing an urgent demand for the advancement of autonomous driving technology. With the continuous increase in labor costs, e-commerce giants such as JD.com, Meituan, and Alibaba have begun to enter the field of unmanned delivery to compete for this one trillion dollar market (Li et al., 2020). As one of the new forces of unmanned driving in China, Neolix has also conducted long-term and outstanding exploration in this field.

This article focuses on a complex scenario faced by Neolix in its actual operation: that is, in areas with narrow passage spaces such as urban traffic auxiliary roads, unmanned delivery vehicles encounter aggressive cut-in during morning and evening peak hours. For example, the cut-in distance of the front vehicle may be less than 0.2 meters. However, at this time, due to traffic congestion and busy roads, unmanned delivery vehicles often have other human drivers closely following behind them (electric vehicles, tricycles, bicycles, etc.) This scenario poses a serious challenge to the longitudinal control strategy of unmanned delivery vehicles: if the unmanned delivery vehicle does not respond in a timely manner or outputs a relatively small braking amount, it is difficult to cope with the possible sudden braking of the cut-in vehicle. On the contrary, if the unmanned delivery vehicle responds too early (exceeding the expectations of the driver of the rear vehicle) or provides too much braking amount, it is high likely to cause the rear end collision due to the follower's delayed response.

In this scenario, the appropriate constraints is a relatively difficult problem to determine. Existing methods may rely on precise predictions or overly simplistic assumptions of the front vehicle, and employ certain fixed constraints to construct optimization problems, such as being at least 0.2 meters away from the nearest vehicle in front (Bageshwar et al., 2004; Yoon et al., 2021). This will result in a larger braking amount output when the constraint is violated. To address this issue, we creatively propose a dynamic constraint method, which constructs this optimization problem based on the result of counterfactual reasoning.

The overall idea and architecture of the method are shown in Fig. 1. Firstly, the acceleration of an unmanned delivery vehicle is calculated based on the initial strategy (such as the previous version of the

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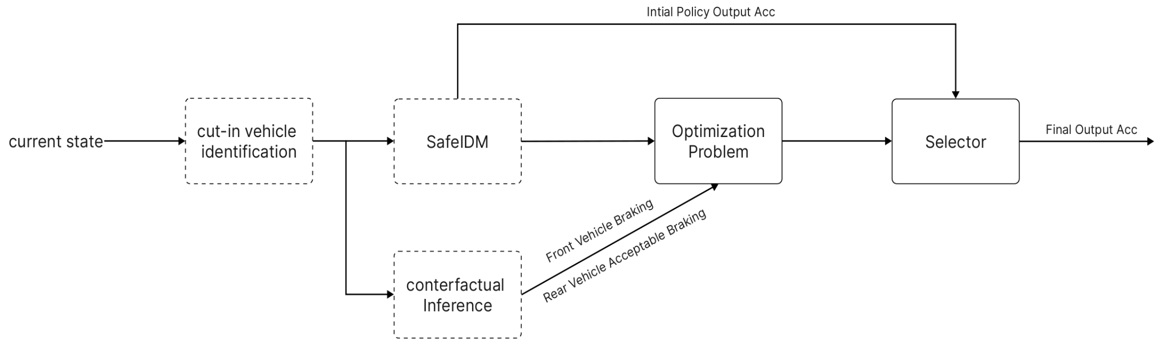

Figure 1: Overall Block Diagram of the CFRLI-IDM Method: We utilize counterfactual inference to deduce the braking intensity of the lead vehicle and the acceptable braking intensity for the following vehicle. This enables the formulation of an optimization problem that incorporates dynamic constraints. By adopting this approach, we ensure the safety of the ego vehicle while simultaneously the safety of the following vehicle to the greatest extent possible.

longitudinal control strategy of the unmanned delivery vehicle), and secondly, we introduce counterfactual reasoning to infer the braking timing and maximum braking amount of the front vehicle, and then the optimization problem based on this inference is solved to obtain a revised output. Finally, a longitudinal control strategy is obtained to ensure the safety of the ego vehicle while ensuring the safety of the following vehicle as much as possible.

The proposed fusion of counterfactual inference and an optimization based approach, has the following advantages:

1. Considered the coping strategy when the safety threshold of the ego vehicle is not satisfied
2. A counterfactual reasoning-based method for inferring the braking timing and maximum braking amount of the preceding vehicle is proposed
3. Building optimization problems based on counterfactual reasoning rather than hand-designed fixed constraints improves the adaptability of this algorithm
4. The solution to the problem can be obtained by analytical solution, reducing the dependence on complex optimizers

In the rest of this paper, Section 2 introduces the RSS model and the method of SafeIDM model, Section 3 introduces the definitions of two hypotheses used in counterfactual reasoning and related counterfactual reasoning method, Section 4 formulates the optimization problem for our longitudinal control strategy of the unmanned delivery vehicle, and the algorithm is given in Section 5, Section 6 describes the design of the simulation scenario and the results of our method, and finally, Section 7 concludes the paper.

2 SafeIDM MODEL

2.1 IDM Model

The IDM model is a longitudinal dynamic model proposed by Martin Treiber and Arne Kesting in 2010 for microscopic traffic flow simulation (Treiber and Kesting, 2010). Due to its low parameter count, strong interpretability and smooth acceleration output, it has been widely used in both simulation scenario generation and real-world vehicle testing over the past decade. The acceleration calculation formula is as follows:

$$a_{IDM}(s,v,\Delta v) = \frac{dv}{dt} = a[1-(\frac{v}{v_0})^{\delta} - (\frac{s^*(v,\Delta v)}{s})^2] \quad (1)$$

In this formula, a_{IDM} represents the acceleration calculated based on the IDM model, s represents the distance between the ego vehicle and the front vehicle, v represents the speed of the ego vehicle, Δv represents the speed difference between the ego vehicle and the front vehicle, a represents the desired acceleration, v_0 represents the desired speed, $s^*(v,\Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$ represents the desired safe distance, and δ represents a parameter.

The IDM model generally works well in the majority of cases, but there are exceptions, and the aggressive cut-in problem discussed in this article is one of them. From the acceleration calculation formula of the IDM model, it can be observed that in aggressive cut-in situations, the front vehicle distance s becomes very small, while the desired safe distance is related to the ego vehicle's own speed and the parameter T. Once the speed is high (resulting in a larger desired safe distance), the term$-(\frac{s^*(v,\Delta v)}{s})^2$ outputs a large negative value, which leads to abrupt braking of the vehicle.

To improve the IDM model, we introduce the RSS (Responsibility-Sensitive Safety) model and use it to calculate a more reasonable desired safe distance (Shalev-Shwartz et al., 2017) (Shalev-Shwartz et al., 2018).

2.2 RSS Model

Definition 1. *(Safe longitudinal distance — same direction) A longitudinal distance between a car c_r that drives behind another car c_f , where both cars are driving at the same direction, is safe w.r.t. a response time ρ if for any braking of at most $a_{max,brake}$ performed by c_f, if c_r will accelerate by at most $a_{max,accel}$ during the response time and from there on will brake by at least $a_{min,brake}$ until a full stop then it won't collide with c_f.*

Lemma 2. *Let c_r be a vehicle which is behind c_f on the longitudinal axis. Let ρ, $a_{max,brake}, a_{max,accel}, a_{min,brake}$ be as in Definition 1. Let v_r, v_f be the longitudinal velocities of the cars. Then, the minimal safe longitudinal distance between the front-most point of c_r and the rear-most point of c_f is:*

$$d_{min} = \left[v_r\rho + \frac{1}{2}a_{max,accel}\rho^2 + \frac{(v_r+\rho a_{max,accel})^2}{2a_{min,brake}} - \frac{v_f^2}{2a_{max,brake}} \right]_+ \quad (2)$$

2.3 SafeIDM

According to the definition of the minimum longitudinal safe distance in RSS, it is possible for the minimum safe distance d_{min} to be very small when the current front vehicle speed is high. Using this definition of safe distance can greatly improve the issue of abrupt braking caused by high speed but small cut-in distances front vehicle in the original IDM model. The desired following distance in SafeIDM can be defined as follows:

$$s^* = 1.1 * d_{min} + s_0 \quad (3)$$

Compared to the original IDM model, the SafeIDM model provides a more reasonable acceleration output when dealing with aggressive cut-in situations. However, this does not guarantee the safety of the vehicle since the IDM model assumes that the acceleration output is highly smoothed (typically using a fourth-order approximation). Additionally, the SafeIDM model does not consider the safety of the rear vehicle. We will discuss viable methods for ensuring safety in longitudinal safety model in Chapter 4 and provide the complete algorithm in Chapter 5.

3 COUNTERFACTUAL INFERRENCE

The longitudinal safety distance of an unmanned delivery vehicle is influenced by various factors, Fig. 2. In the context of this article, inferring the maximum braking amount of the front vehicle can significantly contribute to determining an effective strategy for the ego vehicle to adopt.To address this concern, we present two hypotheses:

Hypothesis 1. *When the front vehicle merges into the lane occupied by the ego vehicle, it is essential to consider the potential occurrence of accidents and the associated liability concern. If, during the merging maneuver, the distance between the front vehicle and the ego vehicle is too small, and the front vehicle abruptly applies the brakes (resulting in a calculated minimum longitudinal safety distance exceeding the current distance), the responsibility for the ensuing accident does not rest with the ego vehicle(as this can be categorized as a deliberate collision).*

Hypothesis 2. *When following the ego vehicle, the rear vehicle should consider the maximum braking amount that the ego vehicle may adopt to maintain a safe distance as much as possible. Compared with unmanned delivery vehicles, human drivers have rich driving experience in complex interaction scenarios, such as aggressive cut-in scenario. Therefore, human drivers adopt the practice of closely following due to the presumption that, in this situation, the ego vehicle does not require the implementation of excessive braking strategies (in the vast majority of cases).*

Based on Hypothesis 1, we can deduce the maximum braking amount that the front vehicle can utilize in aggressive cut-in scenarios by solving the following equation in reverse, resulting in the calculated d_{min} exactly matching the current longitudinal distance between the ego vehicle and the front vehicle.

Similarly, based on Hypothesis 2, we can deduce the maximum braking amount that the rear vehicle assume the ego vehicle may take.

In order to not always use the worst-case assumption, we propeses a graded risk strategy for the inferrence of the braking amount of the front vehicle, which means the braking behavior can be happend in the condition of the longitudinal safety distance is satisfied when the braking amount is in the set of [-0.5, -1, -1.5, -2.0, -2.5, -3, -3.5, -4.0, -4.5, -5] as small as possible(from the perspective of absolute values), if the longitudinal distance between the ego vehicle and the front vehicle is larger than the longitudinal safe distance calculated by the assumption of the front vehicle would brake at the maximum braking amount of

Figure 2: Operation Scenario.

-5, the maximum braking amount of the front vehicle would be assumpted as -5, and then the longitudinal risk level of the ego vehicle is calculated based on this inference result.

4 LONGITUDINAL SAFETY MODEL

4.1 Optimization Problem

To ensure that the acceleration output of the ego vehicle satisfies the safety constraints, we need to consider the output of the SafeIDM model from previous steps as the initial guess for the problem. Based on counterfactual inference, we can obtain the minimum safety distance and the acceptable risk level threshold for the ego vehicle. Using these values, we construct the optimization problem as follows:

$$\begin{aligned} & arg\min_a \frac{1}{2}\|a - a_{ini}\|^2 \\ & s.t. \quad c(s,a) \leq C \end{aligned} \tag{4}$$

Here, a_{ini} represents the output of the SafeIDM model, and c denotes the longitudinal safety signal. We represent it as the ratio of the minimum safety distance to the current distance. $c(s,a) = \frac{d_{min}}{d_{cur}}$ represents the risk level that will occur at the next moment when taking action a in the current state. $d_c ur$ represents the current distance. C represents the acceptable risk level threshold (in this paper, we use $C = 1/1.1$). The solution to this optimization problem allows us to obtain actions that satisfy the risk level threshold constraints while minimizing changes to the original actions.

To solve this problem, we can approximate the dynamic model of the longitudinal risk level using a first-order approximation. This allows us to transform the optimization problem into a quadratic programming problem, namely:

$$\begin{aligned} & a^* = arg\min_a \frac{1}{2}\|a - a_{ini}\|^2 \\ & s.t. \quad c(s) + g * a \leq C \end{aligned} \tag{5}$$

4.2 Risk Level Dynamic Model

Assuming we have knowledge of the maximum braking action taken by the preceding vehicle (inferred from counterfactual reasoning), we can calculate the minimum safe distance required based on the RSS model for the current state. Then, based on our definition of risk, we can determine the risk level of the ego vehicle in the current state. At this point, if we are given the action taken by the ego vehicle and assume that the preceding vehicle will brake with the maximum braking action inferred from counterfactual reasoning, we can calculate the state and the risk level for the next moment (assuming the preceding vehicle continues to brake with the maximum braking action).

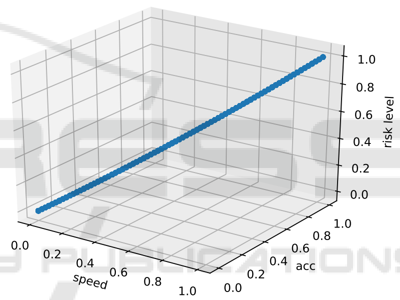

Figure 3: The relationship among speed, acceleration, and risk level is manifested in the following manner: when considering the velocities of the ego vehicle and the lead vehicle, as well as the lead vehicle's braking intensity, the ego vehicle adapts its acceleration accordingly. As a consequence of this adaptation, there is a linear variation in the risk level over a brief future timeframe.

To approximate the dynamics of the risk level in a first-order manner, we sample within the range of accelerations available to the ego vehicle (e.g., with a step size of 0.1). By doing so, we can obtain the risk level for the next moment (e.g., at a time interval of 0.2 seconds). By performing linear regression on this data, we can obtain the first-order approximation coefficient "g" used in the previous formula. To achieve a better linear approximation, we normalize the changes in acceleration and the changes in the risk levels, the result of this approximation can be seen in Fig. 3. This involves transforming the aforementioned first-order approximation into an incremental representation as follows:

$$\overline{c}(s') \approx \overline{c}(s) + g(s;w)^T a \tag{6}$$

$$\frac{(c'-c)-min(c'-c)}{max(c'-c)-min(c'-c)} = \frac{acc-min_{acc}}{max_{acc}-min_{acc}} * g \quad (7)$$

When formulating the optimization problem, we utilize reverse normalization to obtain the constraint representation of the quadratic programming problem. This is expressed as follows:

$$c' = g\frac{a-acc_{min}}{acc_{max}-acc_{min}} * (max(c'-c)-min(c'-c))+c+min(c'-c) \quad (8)$$

Since the current risk level at the present moment is a constant, the maximum change in the safety signal is typically brought about by the ego vehicle applying the maximum braking action, while the minimum change in the safety signal is caused by the ego vehicle applying the maximum acceleration. Therefore, the aforementioned equation can be simplified as follows:

$$c' = g\frac{a-acc_{min}}{acc_{max}-acc_{min}} * (max(c')-min(c'))+min(c') \quad (9)$$

4.3 Optimization Problem Solution

Since the dimensionality of actions in our problem is one-dimensional, representing the acceleration of an unmanned delivery vehicle, and the constraint is a single linear constraint, this optimization problem can be simplified to a quadratic function optimization problem. It can be solved using an analytical solution to obtain the global optimal solution for the problem (Dalal et al., 2018).

Firstly, we can write down the Lagrange equation for the optimization problem based on the constraint and objective function. The Lagrange equation takes the following form:

$$L(a,\lambda) = \frac{1}{2}\left\|a-a_{ini}\right\|^2 + \lambda * (c(s)+g*a-C) \quad (10)$$

Since both the objective function and the constraint are convex, the optimal solution to the problem must satisfy the Karush-Kuhn-Tucker (KKT) conditions, which are as follows:

$$\bigtriangledown_a L = a^* - a_{ini} + \lambda^* * g = 0 \quad (11)$$

$$\lambda^* * (c+g*a^*-C) = 0 \quad (12)$$

Therefore, we obtain the analytical expression for the optimal solution. If λ=0, then $a^* = a_{ini}$. Otherwise, we have $c+g*a^*-C=0$. Substituting this equation into equation (11), we can derive:

$$\lambda^* = [\frac{g*a_{ini}+c(s)-C}{g^T g}]_+ \quad (13)$$

We have utilized normalization to calculate g and substituted it into the result of reverse normalization. As a result, we obtain the final computation:

$$\lambda^* = [\frac{g\frac{a_{ini}-acc_{min}}{acc_{max}-acc_{min}} * (max(c')-min(c'))+min(c')-C}{g^T g}]_+ \quad (14)$$

If $\lambda^* = 0$, it implies that no adjustments need to be made to the initial output. Otherwise, the optimal solution is given by:

$$a^* = a_{ini} - \lambda_i^* g \quad (15)$$

Due to the analytical form of this solution, we can conveniently modify the initial values of the SafeIDM output to ensure that the final output meets our acceptable risk level, without relying on complex optimizers.

5 ALGORITHM

In this section, the complete solution for the complicate cut-in scenario is proposed, this method is based on the basic models introduced in the preceding sections and a method to identify the cut-in intention of the front vehicle.

Firstly, we use SafeIDM model as the initial longitudinal control strategy of the unmanned delivery vehicle and use the definition of lateral safe distance which is also defined by the RSS model to recognize the cut-in vehilce, that is, the front vehicle will be considered as the cut-in vehilce if the lateral safe distance between the ego vehicle and the front vehilce is not satisfied, and then the cut-in coping strategy will be activate.

Secondly, the counterfactual inference method is used to infer the the braking timing and maximum braking amount of the front vehicle. If the current longitudinal risk level is higher than the longitudinal risk threshhold that we can accept, the same counterfactual inferrence method is used to infer the maximum braking amount that the rear vehicle can accept, then the output acceleration of the ego vehilce will be equal to a scaling factor less than 1.0 (in this paper, 0.5 is selected) multiply the maximum acceptable braking amount of the rear vehicle. Otherwise, an optimization problem is constructed based on the inference results, and the control quantity given by the initial strategy is corrected.

We use the longitudinal safety model to correct the output of the initial longitudinal control policy, if the corrected output is greater than zero or the absolute value of the output is smaller than the absolute value of the acceptable maximum braking amount of the rear vehicle, the output is directly sent to the low-level control system. Otherwise, the second corrected output is obtained as the acceptable maximum braking amount of the rear vehicle is used as the initial guess of the longitudinal safety model, the samller absolute value of these two outputs is sent to the control system.

The steps of the proposed algorithm CFRLI-IDM can be summarized as follows.

1. Determine whether the lateral safety distance between the ego vehicle and the front vehicle meets the requirements, if it is ture, the initial outout is unchanged, otherwise, go to step 2.
2. Determine whether the longitudinal safety distance between the ego vehicle and the front vehicle is greater than the needed longitudinal safety distance calculated at the assumption of the front vehicle's maximum braking amount is -0.5, if it is true, go to step 4, otherwise, go to step 3.
3. Obtain the acceptable maximum braking amount of the rear vehicle using the counterfactual inferrence mothod, and output 0.5 multiply this amount.
4. Determine the maximum braking amount of the front vehicle, and obtain the output of longitudinal safety model, if the output is greater than zero or its absolute value is smaller than the absolute value of the acceptable maximum braking amount of the rear vehicle, send the output to control system, otherwise, go to step 5.
5. Use the acceptable maximum braking amount of the rear vehicle as the initial guess as the optimization control problem, and output the smaller absolute value between this output and the output of step 4.

6 EXPERIMENT

We consider an aggressive cut-in scenario, where the initial speed of ego vehicle is 3m/s, the initial speed of front vehicle is 5m/s, so the front vehicle will take over ego vehicle and then take the cut-in action, after a few moment, the front vehicle braking with a random deceleration between -1 and -5, See Fig. 4.

Since the high risk in the scene is mainly related to the acceleration output by the ego vehicle, we tested the acceleration control amount given by different algorithms (IDM, SafeIDM, longitudinal safety model, CFRIL-IDM), as shown in Fig. 5 to Fig. 11.

It can be seen that although in the original IDM model, we used a very small T=0.5s, when the aggressive cut-in occurs, the IDM model still gives a large amount of braking, far exceeding the rear car tolerance level, Fig. 5. Since then, the IDM model lacks protection against the possible sudden braking of the vehicle in front, so it has been in a high-risk area, Fig. 11.

SafeIDM performs better than the original IDM when the vehicle in front has a certain cut-in distance,

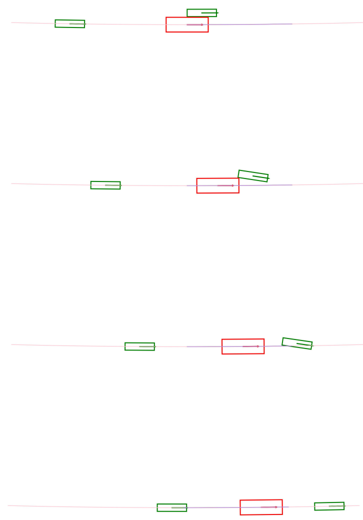

Figure 4: The simulation scenario involves three vehicles, namely the front vehicle, rear vehicle, and ego vehicle. In this scenario, the front vehicle performs an abrupt braking action after performing a cut-in maneuver from the left side of the ego vehicle. The ego vehicle's longitudinal control strategy adopts the CFRLI-IDM model, while the IDM model is utilized for the longitudinal control of the rear vehicle.

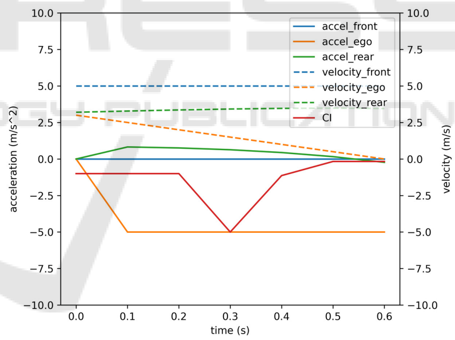

Figure 5: IDM model gives very large amount of breaking in extreme condition.

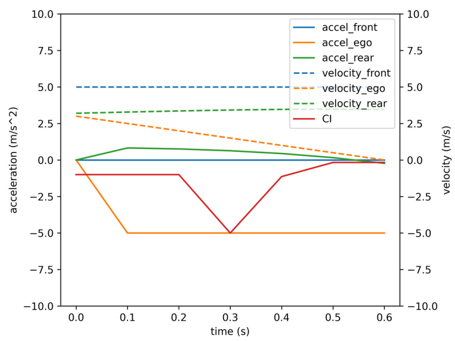

Figure 6: Both the SafeIDM and IDM models are inefficient in dealing with extreme situations.

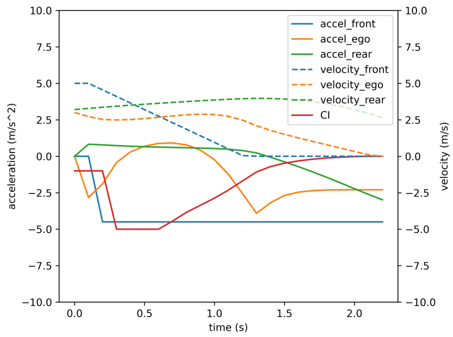

Figure 7: Under non-extreme conditions, the IDM model produces excessive braking levels beyond the acceptable range for the rear vehicle.

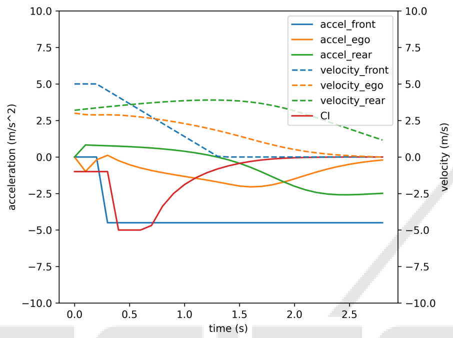

Figure 8: The SafeIDM model outperforms the IDM model in non-extreme situations by providing smoother braking levels for ego vehicle.

Fig. 7, Fig. 8, but it is difficult for SafeIDM to give a good solution when the vehicle in front is too aggressive, such as the detection distance is less than 0.1 meters, Fig. 6.The longitudinal safety model performs well when the vehicle in front cuts in, but as the vehicle in front brakes suddenly, in order to ensure the safety of the ego vehicle, the amount of braking given is still beyond the tolerance of the vehicle behind, Fig. 9. In addition, due to the adoption of the worst-case

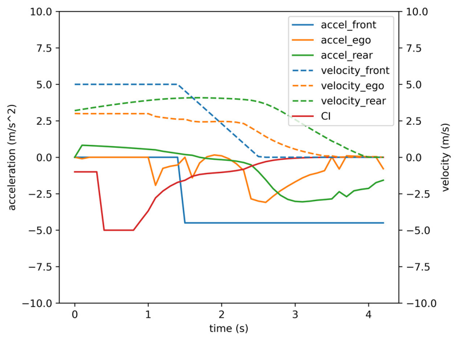

Figure 9: The longitudinal safety model outperforms the conventional IDM model in emergency situations but lacks sufficient protection for the rear vehicle.

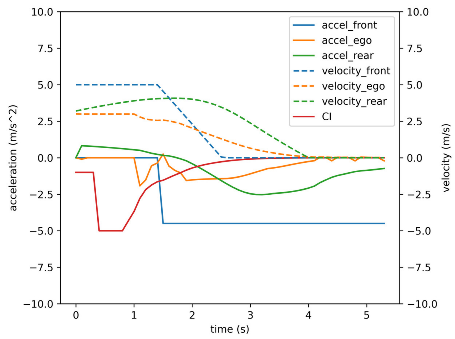

Figure 10: The CFRLI-IDM model effectively protects both the ego vehicle and the rear vehicle in emergency situations.

assumption for the vehicle in front, the response was not timely, resulting in the risk level not being controlled below the threshold of its own acceptable risk level, Fig. 11. As a comparison, the CFRIL-IDM model has always considered the safety of the rear vehicle. Compared with other models, it has the smallest violation of the expectation of the rear vehicle, and gradually makes the braking amount of the ego vehicle consistent with the expectation of the rear vehicle, Fig. 10. At the same time, its own risk level is gradually reduced below the risk threshold, Fig. 11.

7 CONCLUSION

We propose a coping strategy for aggressive cut-in scenarios during rush hours in China by leveraging counterfactual inference. This strategy aims to enhance the adaptability of unmanned delivery vehicles operating in complex urban environments. Our method demonstrates the successful application of causal reasoning within unmanned delivery scenarios. By employing causal inference, we acquire dynamic constraints for optimizing vehicle cooperation and significantly reduce the likelihood of rear-end collisions, a prevalent issue found in accident reports from Waymo. While our method performs effectively in this scenario, there is room for improvement through data-driven approaches. These approaches can be utilized to obtain a more refined initial strategy or incorporate additional information, such as the acceleration of the front-front vehicle (Pourabdollah et al., 2017; Chen et al., 2023). Further research can explore these aspects to enhance the capabilities of our proposed strategy.

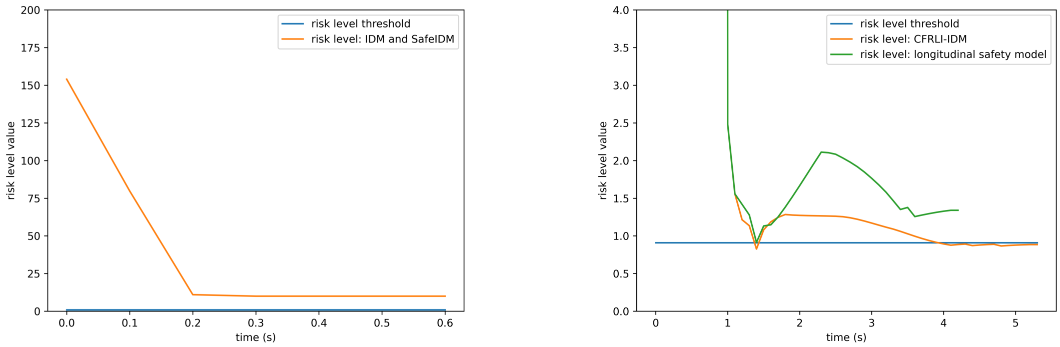

Figure 11: The IDM model and SafeIDM model cannot eliminate the risk of sudden braking from the front vehicle, while the longitudinal safety model partially reduces the risk but does not eliminate it completely. In contrast, the CFRLI-IDM model maintains a lower risk level during cut-in situations and gradually eliminates the risk of sudden braking from the front vehicle.

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