# A Formally Integrated Adaptive Speed Management for Proactive Traffic Safety

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The emergence of connected autonomous vehicles (CAVs) represents a key development in the quest to enhance traffic safety. CAVs hold significant promise for improving traffic safety and have great potential to contribute to transportation sustainability. However, their safety depends on the accuracy of the programmed rules and algorithms that guide their decision-making process. This article introduces an adaptive traffic management system that integrates a formal traffic safety rule defined by pre-established bounds for Traffic Conflict Techniques. This system enables dynamic speed adjustments for vehicles violating the traffic safety rule to prevent potential collisions. To evaluate the effectiveness of our approach, we study a traffic flow on the SR528 highway in Orlando, Florida, and analyze the behavior of each vehicle in traffic based on extracted traffic safety indicators such as time-to-collision and space headway. This analysis is performed by the traffic safety rule to identify violating vehicles, and the speed update is achieved through the integration of the computer algebra system Mathematica and a micro-simulation tool called SUMO. Our study aims to improve the safety and efficiency of the traffic flow by combining simulation, TCTs analysis, and semi-formal tools like Mathematica to aid in the decision-making process of vehicles during traffic events, particularly shockwaves. Preliminary results demonstrate the efficacy of our approach in mitigating the impact of shockwaves. After applying the speed update, we observe an increase in time-to-collision and space headway. This indicates improved safety and reduced likelihood of collisions. Our findings highlight the potential of adaptive traffic management systems to enhance transportation safety and efficiency.

CCS Concepts: • **Theory of computation → Constraint and logic programming**;

Additional Key Words and Phrases: Traffic safety, traffic conflict techniques, adaptive traffic management system, computer algebra, micro-simulation

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## 1 Introduction

Road safety has been a persistent challenge worldwide. Despite numerous efforts to improve road safety, accidents, injuries, and fatalities on the road remain a significant concern. In this context, **Connected and Autonomous Vehicles (CAVs)** [48] have emerged as a potential solution to improve road safety and address some of the challenges associated with human factors in transportation. CAVs are vehicles equipped with advanced sensors, **artificial intelligence (AI)**, and communication technologies that enable them to operate autonomously or with minimal human input. AI-based object detection algorithms play a crucial role in enabling CAVs to collect data, analyze objects, and make accurate decisions while on the road. However, ensuring the safety of CAVs is an ongoing endeavor, as the increasing complexity of these systems poses challenges that require further improvements and advancements. For instance, on February 14, 2016, a Google self-driving car caused its first crash when changing lanes and ended up putting itself in the path of an oncoming bus [14]. In 2021, the **National Highway Traffic Safety Administration (NHTSA)** reported that due to an error in the Full-Self Driving beta software, Tesla recalled approximately 12,000 vehicles [35]. Hence, there is a dire need to guarantee the correctness of CAVs when facing road risks and traffic conflicts. Given that the safety of CAVs is critically dependent on the accuracy of the programmed rules and algorithms, any errors, faults, or inefficiency in these rules can have serious consequences for the vehicle, its passengers, other road users and the entire traffic system. Therefore, it is important to thoroughly verify the correctness of the rules developed to ensure the safe operation of CAVs.

Real-world environments are often more complex than what is stated by traffic rules. Temporary traffic changes due to road work or detours may require adaptive learning and decision-making processes beyond static rule-following. In this context, perception in autonomous vehicles is a critical area of study within the broader field of computer vision, utilizing various sensors and algorithms to enable a vehicle to understand its surroundings, interpret relevant data, and make real-time decisions for safe and efficient navigation. Several studies, such as References [7, 11, 31], explore techniques to enhance autonomous vehicles' ability to detect road users and perceive their surroundings. Liu et al., in Reference [31], propose a motion-aid feature calibration network (MFCN) for video object detection, improving accuracy and training efficiency. Similarly, Cui et al. [11] introduced a multi-object tracking and segmentation data annotation tool called DG-Labeler, which enhances training data annotation. On the security front, Cheng et al. [7] demonstrate an attack framework targeting camera-LiDAR fusion-based 3D object detection models, highlighting vulnerabilities in multi-sensor fusion systems.

However, these approaches also face challenges, such as dealing with uncertainty and sensor noise, where sensor data can be noisy or incomplete due to factors such as poor lighting, occlusions, or adverse weather conditions. Moreover, perception systems, especially those based on machine learning, may struggle to provide guarantees of correctness and safety, which is critical in safety-critical applications like autonomous driving. Fortunately, perception and formal reasoning tools, e.g., Mathematica [33], play complementary roles in autonomous systems. While perception gives the vehicle the ability to dynamically interpret and understand the real-world environment, formal tools provide guarantees about the safety and correctness of specific behaviors. By using formal tools to validate high-level decision-making processes (such as route planning or emergency maneuvers), the vehicle's actions can remain safe, even when the perception systems encounter uncertainty or noisy data.

In the literature, traffic safety rules are typically developed based on a thorough understanding of traffic behavior, traffic flow characteristics, and the interactions between different road users, such as motorists, pedestrians, and public transportation. These rules are often based on data-driven analysis, including crash data, traffic volume data, speed data, and observational studies [1]. While relying on safety rules based on data-driven approaches can have benefits and show general effectiveness, they are deemed unreliable due to their shortcomings, such as the scarcity of collected data as well as the poor quality of available records [54]. In fact, in the case of a human driving, the probability of fatality caused by an accident per one hour is equal to $10^{-6}$ [45]. To foster acceptance of CAVs as viable replacements for conventional vehicles and bolster trust in autonomous transportation systems generally, it is crucial to decrease the fatality rate by a factor of 1,000, achieving a probability of $10^{-9}$ per hour [45]. Achieving this level of confidence is directly linked to the reciprocal of the target probability, specifically $10^{9}$ hours of data, which is equivalent to roughly 30B miles [45]. This attempt to guarantee traffic safety using data-driven approaches is overly simplistic at best. In this context, **Traffic Conflicts Techniques (TCTs)** [54] have emerged to address many shortcomings of the crash data analysis. TCTs are utilized as direct means of evaluating traffic safety by examining their characteristics and observing their occurrences, both during normal traffic flow and in conflict situations [49]. Therefore, leveraging TCTs as a basis for defining traffic safety rules can be effective in enhancing traffic safety [52].

In this study, we develop an adaptive traffic management system that incorporates an automated mechanism for updating vehicle speeds during traffic conflicts. The core of this system is a novel formal traffic safety rule that is defined based on **Time-To-Collision (TTC)** [23], **Space Headway (SHW)** [25], and **Shockwave speed (SWV)** [40], along with their corresponding bounds (cf. Section 3). The correctness of this rule was formally verified in an earlier study [4] using the KeYmaera theorem prover. This rule is proposed to ensure the safe mitigation of traffic conflicts that may arise due to the occurrence of shockwaves. We utilize the Wolfram Language to formalize the traffic safety rule and verify its correctness through computational methods in Mathematica [33]. To do so, we employ the satisfiability checking [2] capabilities of Mathematica to rigorously analyze the rule, identify any potential inconsistencies or unsatisfiable conditions, and refine the rule if necessary. This is particularly useful to ensure that the safety rules are reliable and effective in promoting traffic safety and mitigating traffic conflicts by not violating any important safety constraints. To assess the efficiency of our approach, we utilize the **SUMO (Simulation of Urban MObility)** traffic simulator [32] to simulate a real-life traffic dataset from a highway in Orlando, Florida, and extract relevant data such as vehicle trajectories, speeds, distances, and other TCT information. Subsequently, we integrate Mathematica with SUMO to seamlessly incorporate the traffic safety rule into the SUMO simulation. The interfacing of both tools allows us to apply the rule over the traffic dataset identifying vehicles violating the rule. Leveraging this integration, we implement an adaptive traffic management system that automatically updates the violating vehicles' speeds during traffic conflicts to avoid potential collisions.

**Contributions:** The contributions of this article can be summarized as follows:

- Establishing a traffic safety rule by exploring the link between Time-To-Collision (TTC), Space Headway (SHW), and Shockwave Speed (SWV).
- Formalization and satisfiability checking of the traffic rule using the Mathematica computer algebra system.
- Development of an adaptive traffic management system by integrating formal reasoning, i.e., Mathematica, and real-time monitoring of traffic flow, i.e., SUMO, to provide formal guidance to the decision-making process.

—Application of the adaptive traffic management system over a real-life traffic dataset from highway SR528 in Orlando, Florida.

## 2 Related Work

In 1993, TTC was identified as the main indicator for the design of a collision avoidance system [51]. More recently, in Reference [46], SHW was introduced to describe a safe traffic flow where the shockwave occurrence is unlikely for a series of equal space headways within a platoon of vehicles. The application of TTC and SHW separately to assess traffic safety has been relatively successful. However, combining both indicators can provide more valuable insights from a safety perspective. For instance, in the work done by Essa et al. [17], the developed conflict-based Safety Performance Functions (SPF) aimed to define the relation between rear-end collisions and explanatory variables such as shockwave speed. The main goal was to prove that rear-end collisions mainly take place in shockwave areas where dynamic traffic variables, such as shockwave speed and maximum queue length, are used as indicators. In Reference [6], the main focus of the authors was on investigating the frequency of rear-end crashes in congested freeways in the presence of a downstream shockwave. We conduct in this article an investigation of one of these insights, namely, the impact of TTC and SHW variation on traffic flow.

Traffic regulations, such as the German **Straßenverkehrsordnung (StVO)** [29], which is derived from the Vienna Convention on Road Traffic [20], lay down the rules that all drivers must follow. However, these rules are often vague and open to interpretation, which emphasizes the need for a rigorous (formal), machine-interpretable definition of traffic rules [44]. Such a formalization is crucial for the development of vehicles that always adhere to the rules. Additionally, it may support simulation-based verification. Previous studies, such as the work by Rizaldi et al. in Reference [41], where the authors formalized traffic rules in Higher Order Logic to ensure autonomous vehicles' compliance with these rules, address liability concerns related to collisions involving autonomous vehicles. This was followed by another study [43], where they developed formally proven checkers for safe distance rules to ensure the compliance of CAVs with traffic regulations. In a further effort to engineer CAVs that adhere to safety rules, Rizaldi et al. [42] applied **Linear Temporal Logic (LTL)** to codify overtaking traffic rules in the German traffic rules StVO to provide a verified checker for detecting the occurrence of an overtaking from a trace of a vehicle using the Isabelle/HOL theorem prover. The purpose of this study was to hold autonomous vehicles accountable by formalizing and formally verifying traffic rules as well as clarifying the requirements for designing safe autonomous vehicles. For autonomous vehicles to operate safely and not be held liable in traffic collisions, traffic rules have to be stated clearly by leaving no gap for multiple interpretations. To this end, Maierhofer et al. [34] proposed to extract and infer traffic rules from legal sources and the German road traffic regulations and formalize them using metric temporal logic. To check if the autonomous vehicles abide by these rules, they were evaluated over recorded data on more than 2,500 vehicles. Another approach to achieve the same purpose was proposed in Reference [3], where the authors develop a set of safety contracts and formalize them using **Signal Temporal Logic (STL)** to ensure a collision-free traffic system. These contracts are constructed while ensuring that they are not overly conservative to guarantee the satisfaction of the performance requirements. The robustness of the STL formula trace was demonstrated over synthetic data. In Reference [38], a study was conducted to ensure the safety of lane change maneuvers. To achieve this, the focus was placed on the planned motion and the assumption of redundant hardware. The approach taken involved utilizing formalized traffic rules to identify safe states in vehicle convoys, in compliance with the Vienna Convention on Road Traffic. In Reference [37], the authors proposed a specification-based monitoring approach to define traffic parameters. Furthermore, they employ signal temporal logic as a formal language to analyze these traffic rules. In Reference [39], Rashid et al. opted to formalize some foundation concepts of macroscopic models, namely, density, flow rate, mean speed, relative occupancy, and shockwave using the higher-order-logic theorem prover HOL Light. The studies mentioned above cover the verification of different safety aspects of the vehicle or its interaction with the outer environment. However, none of them has explored the formalization and verification of **Traffic Conflict Techniques (TCT)**, which serve as surrogate safety measures for traffic interactions. Despite the growing complexity introduced by autonomous systems, these works still rely solely on traditional traffic parameters to assess safety. While these parameters have historically been reliable for enhancing safety in the era of human-driven vehicles, they may now be insufficient to fully comprehend the intricate dynamics of autonomous vehicles on the roads. In this study, we present a novel approach defining a new traffic safety rule that CAVs shall abide by. This approach investigates the relationship between traffic indicators, namely, TTC, SHW, and SWV, and their effects on the traffic flow to conduct a TCT-based analysis of road safety.

The concept of adaptive traffic management systems dates to the '90s, where the authors in Reference [10] defined it as an additional intelligent layer to guide the operators to understand traffic state and execute the best strategic control action. In the literature, these systems are applied primarily in two areas: (1) Traffic management optimization at signal lights and (2) Traffic Management System for Optimal Vehicular Navigation. In the former, it involves updating traffic signal schedules based on traffic volume and predicted movements from nearby intersections to reduce travel time and decrease congestion by optimizing the flow of traffic transitions (e.g., References [16, 28, 30]). For instance, in Reference [30], the authors propose a machine learning-IoT based **adaptive traffic management system (ATM)** that aims to reduce travel time and decrease congestion essentially at crossings by constantly updating the traffic signal timing schedule based on the traffic volume state. In the same context, the study conducted in Reference [16] aims to achieve the same objectives of reduced wait time, less congestion, and less pollution by designing and implementing an adaptive traffic system that constantly monitors different road lanes and adaptively changes the traffic lights for the lanes with higher traffic volume and higher waiting time. In another effort to reduce traffic congestion and achieve a smooth traffic flow, the work in Reference [28] introduces a machine learning approach coupled with image processing to manage traffic clearance at the signal junction. For this, the authors developed a self adaptive real-time traffic light control algorithm based on the traffic flow.

In contrast to the above work, in References [5, 22, 53], the focus is on providing the best possible routes for vehicles by analyzing real-time traffic data, road conditions, and other variables to reduce travel time and fuel consumption. To this end, the study in Reference [5] introduces a novel technique for dynamically calculating the shortest route based on the costs of the most optimal roads at different timeslots. Subsequently, the shortest path is identified for each time slot based on the instances of road graphs. A similar approach was proposed in Reference [53] that consists of designing a vehicle rerouting strategy that can adapt itself to the sudden change of urban road traffic conditions. For this, an adaptive Next Road Rerouting (NRR) strategy is developed, which is supported by **vehicular ad-hoc networks (VANETs)** technology that results in considerable gain in terms of trip time reduction and travel time reliability improvement. In Reference [22], the authors propose an adaptive and distributed traffic management system using VANETS based on **Vehicle-to-Vehicle (V2V)** communication and the local view of traffic congestion. Based on the experimental results stated by these studies, their effectiveness was established compared to other approaches, however, none of them explores traffic safety and vehicle interactions during traffic scenarios. To bridge this gap, we propose a formal approach to examine traffic safety in car-following models and to proactively prevent traffic conflicts leading to collisions from occurring.

This is achieved by adopting an adaptive strategy that consists of updating vehicles' speeds depending on the traffic safety indicators' registered values.

Based on these findings and to conduct an efficient and reliable TCT-based analysis, we propose the formalization and satisfiability checking of the traffic safety rule using the computer algebra system Mathematica. Thereafter, we apply this rule to develop an adaptive traffic management system. The system aims to effectively address traffic conflicts, particularly those that occur during shockwaves, by automatically adjusting the speeds of vehicles violating the traffic safety rule within the traffic flow.

## 3 Preliminaries

TCTs evaluate road safety by identifying potential conflicts or near-collisions between vehicles, pedestrians, and other road users. This approach is proactive, as it aims to detect and address potential safety hazards before they result in actual crashes. Below is a brief literature review of the TCTs employed in this work, along with their mathematical formulations.

### 3.1 Time-To-Collision

TTC [23] is a temporal-proximity safety indicator introduced by Hayward in 1971 to identify a potential collision if no preventative measures are taken. TTC is measured in a real-life traffic conflict situation as the duration of time remaining for the collision to occur if no evasive actions occur, and it is considered as an important criterion in traffic conflict techniques. The efficiency of TTC was studied in References [18, 26, 50]. Furthermore, in the study conducted in Reference [24], it was proven that this indicator impacts the speed of the vehicle in one way or another based on a specific threshold chosen to interpret TTC values. According to this study, a TTC value of 4 seconds was considered to indicate a conflict situation. However, it was found that using a TTC threshold of 4 to 5 seconds led to false positives, where potential collisions were indicated even though a normal braking maneuver could have safely mitigated the situation. To address this, it was concluded that a TTC threshold of 3 seconds is more appropriate for reporting serious cases while minimizing the occurrence of false alarms [24].

The mathematical formulation of TTC is given by the following equation [23]:

$$TTC = \frac{x_i - x_{i+1} - L_i}{v_{i+1} - v_i}, \quad v_{i+1} > v_i. \tag{1}$$

In the above equation, the subscripts *i* and *i+1* represent the leading and following vehicles, respectively. The variables $x_i$, $x_{i+1}$, $v_i$, and $v_{i+1}$ refer to the positions and velocities of the two vehicles, while $L$ represents the length of the leading vehicle ($i$).

### 3.2 Space Headway

SHW [25] is defined as the physical distance separating two consecutive vehicles. SHW quantifies the distance between the front of two consecutive vehicles in a traffic flow. Mathematically, SHW is defined as the positional difference between vehicle *i* and *i+1* and can be expressed as [25]:

$$SHW = x_i - x_{i+1}, \tag{2}$$

where the variables $x_i$ and $x_{i+1}$ refer to the positions of the leading vehicle ($i$) and the following vehicle ($i+1$), respectively.

### 3.3 Shockwaves

**Shockwaves (SWV)** [40] are defined as byproducts of traffic congestion and queues. Furthermore, they represent the transition zones between two traffic states that move through a traffic environment. In the literature, it is used as an existing event where the analysis takes place after its occurrence. This traffic phenomenon occurs due to various factors such as a signalized intersection, aggressive lane changes, or a collision downstream of a platoon of vehicles. This event is characterized by a sudden slow-down or halt of vehicles, leading to a platoon of stationary or slowed vehicles on a particular section of the road. To detect the occurrence of shockwaves mathematically, the SWV speed can be computed over a range of consecutive vehicles. The formula for calculating SWV in the macroscopic model can be expressed as [46]:

$$SWV = \frac{\dfrac{v_i}{SHW_i} - \dfrac{v_j}{SHW_j}}{\dfrac{1}{SHW_i} - \dfrac{1}{SHW_j}}, \tag{3}$$

where the variables $v_i$ and $v_j$ correspond to the speeds of vehicles $i$ and $j$, respectively. Additionally, $SHW_i$ and $SHW_j$ represent the distances between vehicles $i$ and $i+1$ and vehicles $j$ and $j+1$, respectively. It is important to note that $i$ and $j$ are distinct vehicle indices such that $i \neq j$.

## 4 Proposed Methodology

Car-following models [21] are reflected by platoons of vehicles where every vehicle can be a leader and/or a following vehicle. In this model, rear-end crashes occur frequently due to different traffic events. The study in Reference [6] identified shockwaves as a traffic conflict leading to the occurrence of rear-end crashes. In the literature, shockwaves are defined as traffic events that occur due to predicted and/or unpredicted changes in the traffic state, such as crashes and intersections [40]. The SWV speed indicator serves as an indicator for the presence of shockwaves. To further study the impact of shockwaves on the traffic flow, we analyze the fluctuations in two significant TCTs, namely, TTC and SHW. These metrics are known to reflect minor disruptions in the traffic flow. Analyzing the correlation between TTC, SHW, and SWV is undertaken with the goal of enhancing traffic safety by predicting future traffic conflicts and implementing appropriate measures to prevent them. The sketch of the traffic safety rule is given below:

$$\text{Violated Indicators}(Ind_{violated}) \longleftrightarrow \text{Shockwave Occurrence}(SWV_{speed}), \tag{4}$$

where *Violated Indicators* and $SWV_{speed}$ represent TTC, SHW violating their respective bounds, respectively. In this sketch, we examine the bidirectional causal relationship between SWV speed, TTC, and SHW. Specifically, we investigate how violating the TTC and SHW thresholds affects the occurrence of shockwaves and how the shockwave speed impacts the TTC and SHW indicators.

As depicted in Figure 1, we start by expressing the traffic safety rule along with the speed adaptation control in the Wolfram language of Mathematica [33]. As shown in Figure 1, the traffic simulator SUMO must be provided first with a calibrated dataset. We use traffic-related data extracted from loop detectors, allowing the detection of vehicles passing or arriving at certain points, positioned on a 2-mile section of the SR528 highway in Orlando, Florida, covering both east- and west-bound traffic [47]. Upon the traffic simulation, the vehicles' dynamics, such as speeds, accelerations, space headways, and TTCs, were collected for each detector and aggregated for 1 minute.

To achieve a seamless integration between Mathematica and SUMO, the **Application Programming Interface (API)** provided by Mathematica allows for a flexible connection between the two systems, as illustrated in Figure 1. This integration enables the development of an adaptive traffic management system to reduce traffic conflicts by detecting violating vehicles and updating their speed. The proposed system incorporates a speed adaptation mechanism that adjusts the

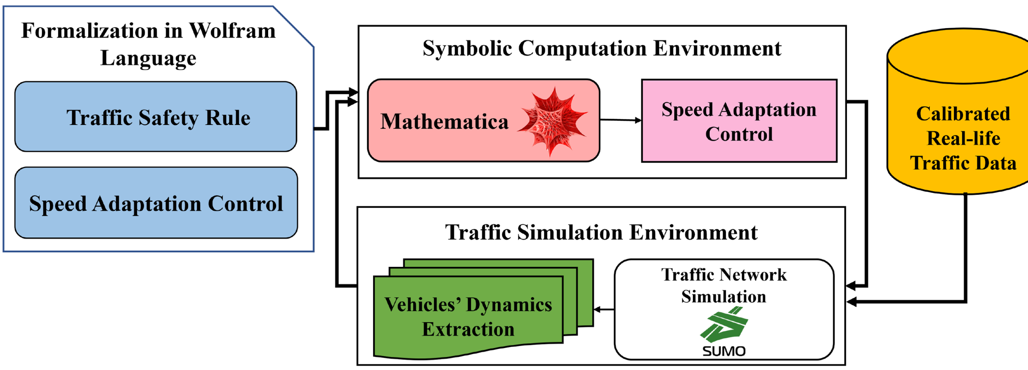



Fig. 1. Methodology of Adaptive Traffic Management System.

speed of new vehicles joining the queue when the safety traffic rule is violated. This adaptation is achieved by assigning appropriate acceleration/deceleration values to safely mitigate the traffic conflict. Depending on the assigned acceleration/deceleration, the speed of the violating vehicle can be increased, decreased, or maintained at the same level. Once the speed update is performed, the traffic simulation is re-run to reflect the changes in the platoon. This feedback loop established between Mathematica and SUMO, as depicted in Figure 1, enables the continuous updating of the traffic simulation based on the adjustments made through the speed adaptation mechanism where it proves its efficiency by reducing upcoming traffic conflicts due to the early notice informing the vehicles about the traffic state ahead.

## 5 Integrating Computer Algebra and Micro-simulation

To implement the adaptive traffic management system, we utilize the computer algebra tool Mathematica to define the traffic rule in the Wolfram Language. Mathematica offers the advantage of interfacing with other tools, such as SUMO, which facilitates data exchange and sequential execution of multiple tasks. In this context, the specificity of this study lies in integrating Mathematica with SUMO to allow the execution of Wolfram Language programs within the traffic simulation framework.

To reduce traffic conflicts and avoid future crashes, the introduced adaptive traffic management system is established through a set of steps described as follows:

(1) Sumo is selected as the traffic simulation engine, and calibration is performed using real-life data. This allows us to specify the dynamics of vehicles at each timestep and the IDs of their leading vehicles; both input to Mathematica. The extraction of vehicles' dynamics from the traffic simulation in SUMO is given by Listing 1, where `sumoTTC` and `spaceHeadway` represent the TTC and SHW between the current vehicle and its predecessor, respectively. As for `egoSpeed`, `veh`, and `leaderID`, they represent the speed, vehicle ID, and leader vehicle ID of the current vehicle, respectively, in the traffic simulation.

    The vehicle dynamics along with the TCTs extraction is rendered possible due to the function defined in Mathematica, i.e., *ExternalValue*, that returns the value of the specified parameter from an external evaluation session. In Listing 2, line 1 retrieves the TTC value from the SUMO simulation session and stores it in the variable `TTC`. Line 2 fetches the SHW value from the simulation and assigns it to the variable `SHW`. Line 3 obtains the vehicle's current speed and stores it in `Initial_Speed`. Line 4 retrieves the vehicle's ID and assigns it to the variable `vehID`. Finally, line 5 retrieves the ID of the leading vehicle and stores it in the variable `leaderID`.

```
    for veh in allvehicles:
        leader = traci.vehicle.getLeader(veh)
        if(leader):
            leaderID = leader[0]
            spaceHeadway = leader[1] + traci.vehicle.getMinGap(veh)
            leaderSpeed = traci.vehicle.getSpeed(leaderID)
            egoSpeed = traci.vehicle.getSpeed(veh)
            egoAccel = traci.vehicle.getAcceleration(veh)
            if (egoSpeed - leaderSpeed) != 0:
                sumoTTC = (spaceHeadway) / abs(egoSpeed - leaderSpeed)
```

Listing 1. Retrieving Vehicle Dynamics from SUMO.

```
TTC:=ExternalValue[psession,"sumoTTC"];
SHW:=ExternalValue[psession,"spaceHeadway"];
Initial_Speed:=ExternalValue[psession,"egoSpeed"];
vehID:=ExternalValue[psession,"veh"];
leaderID:=ExternalValue[psession,"leaderID"]
```

Listing 2. Retrieving Vehicle Dynamics from SUMO using Mathematica.

```
If[SHW < 1/k && TTC < 3, Speed := sp, Speed := Initial_Speed];
```

Listing 3. Conditional Assignment of Speed for Violating Vehicles using Mathematica.

```
traci.vehicle.slowDown(veh, sp, 0.0)
```

Listing 4. Calling the slowDown Method in TraCI.

(2) Subsequently, we identify the vehicles violating the traffic rule to update the speed value. The vehicle will either accelerate or decelerate to reach the assigned speed. As shown in Listing 3, the safety indicators—TTC and SHW—are compared against predefined thresholds to identify any vehicles violating safety rules. Once a violation is detected, the speed is adjusted to restore safety. In the subsequent Listings, our implementation is generalized by defining variables such as k, which denotes the traffic flow density given by the number of vehicles in the platoon, and sp, which represents the updated speed value. These variables can only be specified in concrete examples when the number of vehicles is known and the exact speed required to maintain traffic safety can be determined.

(3) After assigning the new speed value, the traffic simulation in SUMO resumes its execution by reading the new assigned speed and updating the vehicle's dynamics dynamically. As indicated in Listing 4, the updated speed is represented by `sp`, and the third argument, `0.0`, specifies to the duration for the change to take place.

(4) Consequently, the vehicle dynamics are extracted through SUMO, where the change made is prominent. After analyzing the data, we notice the impact of the speed variation on the traffic flow, most importantly on the vehicles belonging to the platoon.

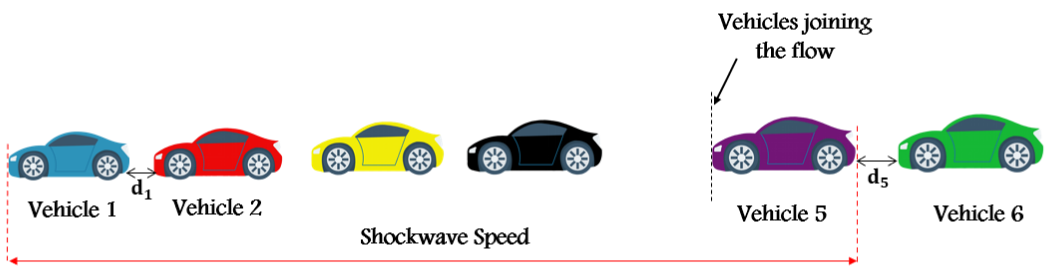



Fig. 2. Illustration of Vehicle Platooning.

## 6 Traffic Safety Rule Specification

In this section, we present a formal definition of the TCTs used in the study, namely, TTC, SHW, and SWV, using the Wolfram Language. We also include the formalization of the traffic safety rule. Additionally, we present the formalization of the speed adaptation process, which will be implemented using SUMO in the subsequent steps. Car-following models account for the variability in the number of vehicles that can form a platoon as shown by Figure 2, which may depend on factors such as traffic flow, time of day, and the type of road, such as whether it is a highway or a local road. Therefore, we reason about a generic number of vehicles during the formalization using universal quantifiers.

### 6.1 Formalization of TCTs in Mathematica

Using their mathematical representations, we formally define TTC, SHW, and SWV to provide the formal definition of *Violated Indicators* and *Shockwave Speed* as given by the rule sketch 4.

*Definition 1. Violated Indicators ($Ind_{violated}$)*

$$\vdash \texttt{ForAll i ForAll j } ((i \neq j)\ \&\&\ (TTC < 3)\ \&\&\ (SHW < \frac{1}{k})),$$

where *ForAll[x, expr]* corresponds to the symbol ∀ in mathematical notation. It is typically used in logical expressions to express that a statement, i.e., *expr*, is *True* for all values of a certain variable, i.e., *x*. The symbol "&&" is used to represent the logical conjunction (logical "and") operation and $k$ being the density of the traffic flow. The condition $i \neq j$ is included in the definition to ensure that we consider all vehicles and their respective following vehicles in our analysis. Based on Definition 3, a TTC of less than 3 seconds, accompanied by an SHW less than the inverse of the traffic flow density, will have noticeable implications on traffic flow.

*Definition 2. Shockwave Speed ($SWV_{speed}$)*

$$\vdash \texttt{ForAll i ForAll j } ((i \neq j)\ \&\&\ (0 \leq SWV \leq 7)\ ||\ (SWV < 0)),$$

where the symbol || is used to represent the logical disjunction (logical "or") operation. According to the research conducted by Ibrahim et al. in Reference [27], the presence of a shockwave can be identified by calculating its speed. Specifically, a shockwave speed of 7m/s (equivalent to 25.2km/h) between the ith and jth vehicles in a platoon of vehicles, where $i \neq j$ is indicative of a shockwave occurrence. The sign of the speed value determines the direction of the shockwave propagation, and it can propagate either upstream or downstream. Specifically, the following cases apply:

— When SWV < 0, the shockwave propagates in the same direction as the traffic stream, i.e., upstream.
— When SWV ≥ 0 and SWV < 7, the shockwave propagates against the traffic stream, i.e., downstream.

### 6.2 Formalization of the Traffic Safety Rule in Mathematica

By utilizing Definitions 3 and 4, we can provide a detailed explanation of the proposed safety rule that connects the traffic safety indicators, as outlined below.

Theorem. *Traffic Safety Rule*

```
⊢ ForAll i
  ForAll j
  (i ≠ j) && (TTC < 3) && (SHW < 1/k) ⟷ (SWV < 0) || (0 < SWV < 7)
```

For a TTC and an SHW below their respectful thresholds, the occurrence of shockwaves is confirmed based on the bounds set for the SWV speed and vice versa. To identify vehicles violating this rule, we prioritize the vehicles belonging to a platoon, where a slight modification of the vehicle's dynamics are automatically reflected by the following vehicles as depicted by Figure 2. Therefore, we formalize the safety rule and prove its correctness using the built-in function of Mathematica **SatisfiableQ** [33]. This function takes a logical expression or a set of logical expressions as an argument, i.e., *expr*, and returns *True* if the expression is satisfiable, meaning that there exists a combination of truth values for the variables that make the expression true. If the expression is not satisfiable, then the function returns *False*.

### 6.3 Formalization of the Speed Adaptation Mechanism in Mathematica

Implementing the speed adaptation process using Mathematica and the traffic simulator SUMO represents the core of the adaptive traffic management system. Integrating both tools allows for evaluating the traffic safety rule satisfaction by the vehicles present in the simulation. In this context, the adaptive traffic management system aims to control the vehicle's dynamics by employing the speed adaptation process to update the vehicles' speed to reach a target speed as given by Algorithm 1. By interfacing Mathematica with the traffic simulator SUMO, the rule evaluation is carried out for all vehicles in the simulation using the universal quantifier (ForAll), where *a(i)* represents the acceleration of vehicle *i*, and *A* and *D* are two positive variables representing deceleration rates assigned to the vehicles.

Based on its formalization depicted by Algorithm 1, the identified vehicle is evaluated according to its TTC and SHW values. If these values exceed the specified thresholds, then the vehicle should decelerate accordingly to avoid conflicts, which is translated by assigning a deceleration rate to the vehicle in question to reduce its speed. However, if the computed values of the traffic safety indicators, i.e., TTC and SHW, are not violated, then we choose either to maintain the current vehicle's speed or allow it to accelerate, (lines 1–3 and line 9).

For instance, if a TTC is less than 3 or SHW is less than $1/k$ because of the speed adaptation process, then the speed is decreased by assigning a negative acceleration value to the vehicle, i.e., forcing the vehicle to decelerate to adapt to the traffic flow and avoiding the formation of shockwaves (lines 5–7). However, if the shockwave speed falls within the designated range that confirms its occurrence, then the traffic adaptation system will direct new vehicles joining the queue to reduce their speed, (lines 11–13). Conversely, if the shockwave speed does not fall within this range, then the vehicles will continue to travel at their current speed without any adjustments (lines 14–16). Through continuous traffic simulation, we can monitor how changes in traffic flow

Fig. 3. SR528 Highway in Orlando, Florida.

**ALGORITHM 1**: Speed Adaptation Mechanism

```
if((SHW ≥ 1/k) || (TTC > 3))
then
    (ForAll i. a(i) := A)
else
    if((SHW < 1/k) && (TTC ≤ 3))
    then
      (ForAll i. a(i) := -D)
    else
      (ForAll i. a(i) := 0)
     fi;
     if((SWV < 0) || (0 ≤ SWV ≤ 7))
     then
       (ForAll i. a(i) := -D)
     else
       (ForAll i. a(i) := A)
     fi
fi
```

are affected by the speed fluctuations of vehicles that violate traffic safety regulations, which may be caused by external factors impacting the traffic.

## 7 Case Study: SR528 Highway

### 7.1 Description of the SR528 Highway

To analyze the TCTs variation of every vehicle, we closely monitor the traffic flow in real-life using traffic-related data extracted from loop detectors. These detectors allow us to detect when vehicles pass or arrive at specific points located along a two-mile stretch of the SR528 highway in Orlando, Florida, encompassing both east and westbound traffic, as shown in Figure 3. The simulation model development and model calibration were done in compliance with the standards established by the US Department of Transportation. Finally, the simulation model was assessed using data from actual traffic [15]. The traffic volume was used to calibrate the study's parameters. In this work, **Geoffrey E. Heavers (GEH)** statistics [19] were used to calibrate the model. This considers both the absolute value and the percentage difference. GEH determines the model's goodness of fit [19]. The formula to determine GEH is as follows:

$$GEH = \sqrt{\frac{2(V_{obs} - V_{sim})^2}{(V_{obs} + V_{sim})}}. \tag{5}$$

The traffic volumes of the detectors in the simulation are represented by $V_{sim}$. If the value of GEH is less than 4 for the total number of cars in all of the links, i.e., on-ramps, off-ramps, and freeways in between, then the simulation model is judged to be a good fit [15]. For this investigation, the GEH value for the calibrated parameters was 1.26. This value indicates that the simulated vehicle volume matches the actual field volume.

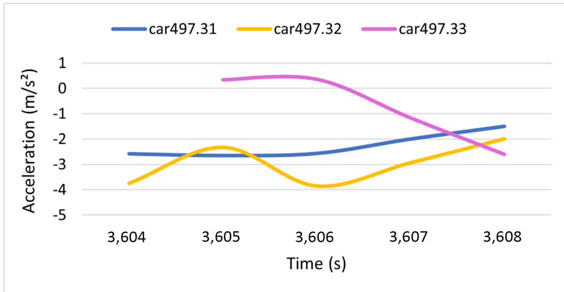
To verify the simulation model, we use the average field speed aggregated for 1 minute from the detectors. The absolute difference between simulation speed and field speed must be less than 5 mi/h in 85% of the cases [36]. In 93% of the situations in our model, the absolute speed difference between the detectors' simulated average speed and field average speed was less than 5 mi/h. This result implies that the developed traffic simulation model is accurate and compatible with actual traffic conditions, supporting its validity.

### 7.2 Results, Discussion, and Limitations

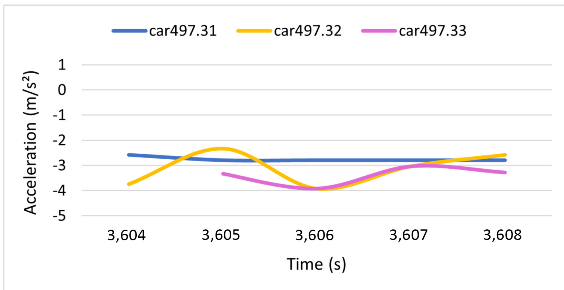
Observing changes that impact the traffic flow in a calibrated real-life traffic data dataset can be challenging due to the large number of vehicles. To simplify the analysis, we apply the proposed safety rule that integrates the speed adaptation process on a platoon of vehicles. Using the traffic simulator SUMO, we analyze the data extracted from this highway and identify various congested regions that are the primary focus of our case study. Furthermore, these periods of congestion allow us to conduct a detailed analysis of TCTs, SHW, and SWV and accurately evaluate the effectiveness of the traffic safety rule. To identify violations of this traffic rule, we extract the initial vehicle dynamics from two samples of platoons. For each vehicle in the platoon, we obtain its speed and acceleration along with the ID and speed of its leader vehicle. Additionally, we extract traffic safety indicators, such as TTC and SHW, for every two consecutive vehicles in the platoon.

*7.2.1 Results.* We have selected two platoons as candidates for implementing the speed adaptation control process and evaluating its effectiveness. The traffic simulation in SUMO is initiated by selecting the first vehicle from the platoon that violates the safety rule and applying a speed adaptation process to reduce traffic conflicts and improve traffic flow. This process involves assigning a new speed value to the identified vehicle, which decelerates smoothly for three seconds until it reaches the target speed. The deceleration affects the behavior of the other vehicles in the platoon, causing them to adjust their speeds gradually. We repeat this process for two platoons and present the results by comparing the acceleration, SHW, and TTC profiles of the original and updated platoons.

***Platoon 1.*** To investigate the efficiency of the speed adaptation control process, we focus on a platoon consisting of five vehicles and study its behavior over a period of four seconds, from timestep 3,604 to 3,608. Among the five vehicles, we identify "car497.31" as the one violating the rule at timestep 3,605. Therefore, timestep 3,605 marks the moment at which the speed adaptation control process is applied.




(a) Acceleration Profile of the Original Platoon



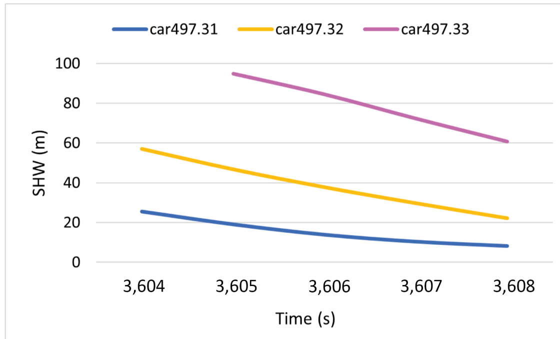

(b) Acceleration Profile of the Updated Platoon

Fig. 4. Acceleration profile of platoon 1.

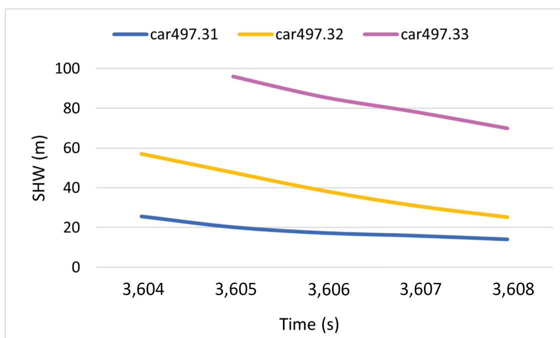
Table 1. Improvement Statistics of the Adaptive Traffic Management System

| Platoon | Timestep | Improvement Rate | | |
|---|---|---|---|---|
| | | Acc | SHW | TTC |
| Platoon 1 | 3,605 | 9.7% | 8.8% | 1.2% |
| | 3,606 | 10.2% | 27.8% | 70% |
| | 3,607 | 63.1% | 66% | 188.9% |
| | 3,608 | 140.6% | 102.7% | 265.8% |
| Platoon 2 | 3,605 | 51.6% | 3.5% | 150% |
| | 3,606 | 243.3% | 102.4% | 250% |
| | 3,607 | 327.7% | 95.5% | 275.5% |
| | 3,608 | 269.7% | 16.9% | 290.8% |

***Acceleration Profile.*** By comparing the acceleration profile of the original platoon shown in Figure 4(a) with the updated platoon's acceleration profile in Figure 4(b), the impact of the speed update can be observed. The behavior of the following two vehicles of "car497.31," namely, "car497.32" and "car497.33," has changed compared to the original platoon's acceleration profile. The change in behavior is characterized by a deceleration that starts at timestep 3,605 with a decrease rate of 9.7%. At timestep 3,606, the decrease rate is 10.2%, followed by a 63.1% decrease at 3,607. By timestep 3,608, the decrease rate is 140.6%, reflecting the deceleration of the vehicles after the speed update compared to their acceleration before the speed update, as shown by Table 1. This decrease in acceleration illustrates the vehicles' deceleration to reduce their speed and achieve a target speed due to the evaluated conflict.




(a) Space Headway Profile of the Original Platoon



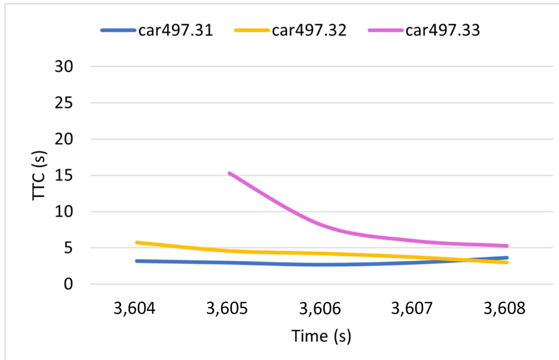

(b) Space Headway Profile of the Updated Platoon

Fig. 5. Space headway profile of platoon 1.

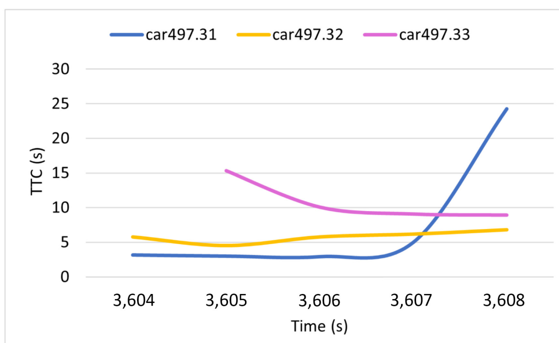
***Space Headway Profile.*** To further investigate the impact of speed adaptation control on the platoon, a SHW profile analysis is conducted. Figure 5(a) shows the SHW profile of the original platoon, indicating a decrease in the SHW values of the three studied vehicles over time. Figure 5(b) shows the updated platoon SHW profile for the three vehicles, including “car497.31,” which undergoes a speed update at timestep 3,605. The difference between the presented SHW profiles is evident in Figure 5(b), where the SHW values of each vehicle show a gradual increase for each timestep compared to the original space headway values. For instance, at timestep 3,605, there is an increase rate of 8.8%, which increases to 27.8% at timestep 3,606. At timesteps 3,607 and 3,608, the increase rates of SHW values are 66% and 102.7%, respectively, as shown by Table 1.

***Time To Collision Profile.*** The impact of the studied speed update on the platoon can be seen in the TTC values for the vehicles, where a variation in TTC is observed. The TTC profiles for the platoon before and after the speed update are shown in Figures 6(a) and 6(b), respectively. Compared to the original TTC values, the new values indicate an increase due to the speed adaptation process. This change is reflected in the TTC profiles presented in Figures 6(a) and 6(b), where a 1.2% increase rate is noted at timestep 3,605. By timestep 3,606, the increase reaches 70%, while at timesteps 3,607 and 3,608, the vehicles achieve a total increase of 188.9% and 265.8% in TTC values, respectively, as shown by Table 1. This increase in TTC values is the goal of the speed adaptation control process when traffic conflicts are detected.

***Platoon 2.*** In this scenario, a platoon of eight vehicles is being monitored over a period of five seconds. During this time, a specific vehicle named “car457.22” is identified as violating with a TTC




(a) Time To Collision Profile of the Original Platoon



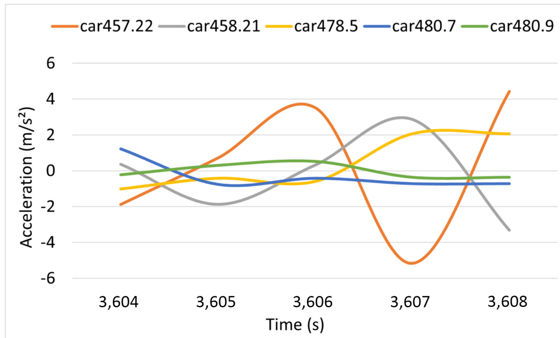

(b) Time To Collision Profile of the Updated Platoon

Fig. 6. Time-To-Collision Profile of Platoon 1.

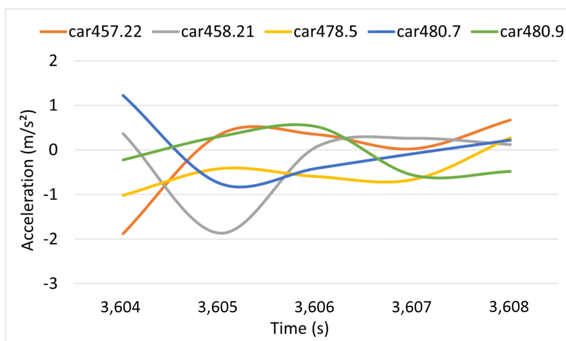
of less than 3 at timestep 3,604. Our focus is on the five vehicles following the violating car, and we have been provided with their acceleration profile, SHW profile, and TTC profile. The analysis of these profiles is done for timesteps from 3,604 to 3,608, but the impact of the speed update is observed starting from timestep 3,605.

***Acceleration Profile.*** Figure 7(a) shows the acceleration profile of the vehicles in the platoon before the speed update. The acceleration profile of "car457.22" is unstable, with sudden peaks and drops in response to changes in traffic conditions. At timestep 3,608, its acceleration abruptly increases to above 4 $m/s^2$. However, after the speed update, the acceleration profile of "car457.22" is smoother and exhibits a gradual increase that remains below the original values for each timestep, as shown in Figure 7(b). The impact of the speed update is observed progressively over time, where the percentage decrease indicates significant improvements. For example, at timestep 3,605, a decrease of 51.6% is achieved, while at timestep 3,606, the decrease is 243.3%. Additionally, at timesteps 3,607 and 3,608, the decrease rates are 327.7% and 269.7%, respectively, as shown by Table 1.

***Space Headway Profile.*** Figures 8(a) and 8(b) show the SHW profile before and after the speed adaptation process, respectively. The figures demonstrate that the speed adaptation process increases the SHW values for all vehicles in the platoon. Prior to the speed update, "car457.22" had a negative SHW value below −2 m, indicating an imminent crash that occurred at timestep 3,606, as shown in Figure 8(a). However, applying the speed adaptation process at timestep 3,605




(a) Acceleration Profile of the Original Platoon



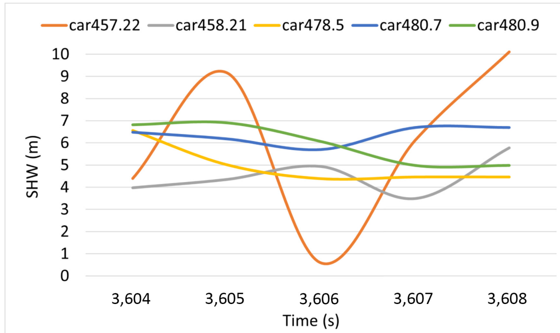

(b) Acceleration Profile of the Updated Platoon

Fig. 7. Acceleration Profile of Platoon 2.

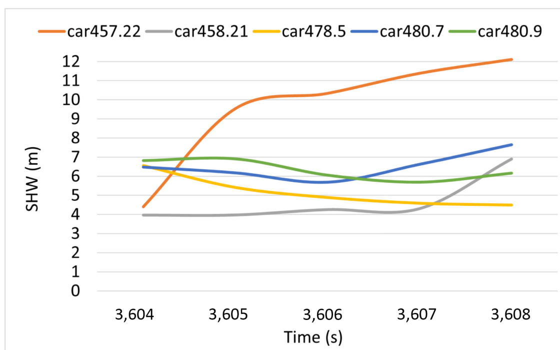
prevented the crash by increasing the SHW to 1.3 m, as reported by Figure 8(b). This improvement is observed for all vehicles in the platoon and is confirmed by the percentage increases computed for each timestep. At timestep 3,605, the SHW values increased by a total of 3.5%. Additionally, at timestep 3,606, there was a 102.4% increase in SHW, while at timestep 3,607, the increase was 95.5%. Finally, at timestep 3,608, the increase rate was 16.9%, as shown by Table 1.

***Time To Collision Profile.*** The effect of the speed adaptation process on TTC values of the vehicles in the platoon is investigated by analyzing the TTC profiles presented in Figures 9(a) and (b). The increase of the TTC values for each vehicle in the platoon is apparent in Figure 9(b) after executing the speed update process, compared to the TTC profile before the adaptation process in Figure 9(a). Moreover, the percentage increase rate of TTC for every timestep is computed to quantify the improvement. We observed a 150% increase in TTC values at timestep 3,605, while at timestep 3,606, the TTC values increased by 250%. Additionally, an increase rate of 275.5% and 290.8% was achieved at timesteps 3,607 and 3,608, respectively, as shown by Table 1.

*7.2.2 Discussion.* In summary, the efficiency of the traffic safety rule in detecting traffic conflicts has been demonstrated by integrating SUMO and Mathematica. Upon identifying the violating vehicle, the corresponding vehicle platoon is analyzed, and a speed adaptation process is implemented to modify the vehicle's speed. The impact of this adjustment is assessed by examining the acceleration, TTC, and SHW profiles of the vehicles within the platoon. This analysis is performed on two platoons where conflicts are detected. The findings reveal a notable enhancement in TTC and SHW values, indicating a reduction in the occurrence of conflicts when the




(a) Space Headway Profile of the Original Platoon



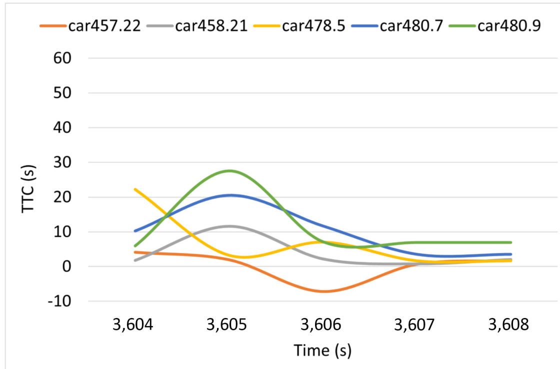

(b) Space Headway Profile of the Updated Platoon

Fig. 8. Space Headway Profile of Platoon 2.

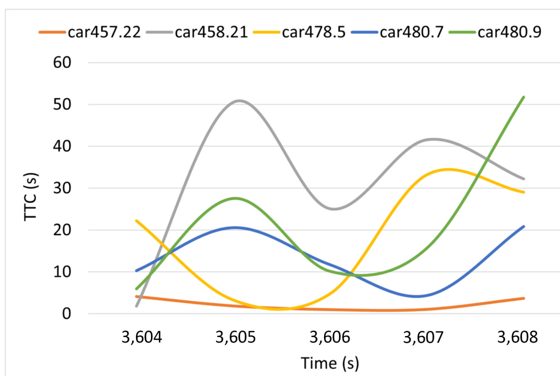
speed adaptation process is applied. For instance, in Platoon 1, the initial count of conflicts was 3,523. However, after applying the speed update, the conflicts were reduced substantially to 264. Similarly, for Platoon 2, the number of conflicts decreased to 523.

The speed adaptation mechanism took place, thanks to the integration of SUMO and Mathematica. The implementation and the simulation was running in Windows 10 Pro OS on a computer with Intel(R) Core(TM) i7-1065G7 CPU @ 1.30 GHz and 16 GB of RAM. We initially start by executing the Mathematica script, which subsequently launches the SUMO simulation. During each simulation step, data is retrieved and sent to variables defined in Mathematica, where the traffic safety rule is evaluated at every timestep. Based on the outcome of this evaluation, a speed update is performed by sending the new speed value to SUMO, which then applies it to the corresponding vehicle in the simulation. The implementation of this adaptation process in CAVs in real-time can be achieved for one-to-one vehicle situations, where the vehicle will only consider the dynamics of its predecessor vehicle (leading vehicle). During car-following models, this can prove efficient and introduce a proactive approach that helps to avoid traffic conflicts. However, on a larger scale, adding V2V communication will help generalize this approach for various traffic scenarios other than car-following such as four-way traffic intersections (signalized/unsignalized).

*7.2.3 Limitations.* The approach we propose in this work can be generalized over car-following models where we can identify platoons of vehicles. This includes highways, queues at traffic intersections, and congested roads. One limitation of this case study is the difficulty to monitor the




(a) Time To Collision Profile of the Original Platoon




(b) Time To Collision Profile of the Updated Platoon

Fig. 9. Time-To-Collision Profile of Platoon 2.

behavior of the same vehicles over time due to the continuous cutting in and out of the platoon by the vehicles.

Another limitation of this approach consists of the size of the platoon. In fact, our approach's efficiency is best demonstrated over a large-sized platoon, however, it will be computationally expensive to consider all the data we have, in addition to the long simulation time. Furthermore, an extra challenge lies in the interfacing between Mathematica and SUMO, where it becomes unstable and lags, where eventually, the Mathematica session times out.

## 8 Conclusion

**Connected Autonomous Vehicles (CAVs)** have the potential to revolutionize transportation by reducing congestion, optimizing traffic flow, and enhancing overall safety. However, the safety of CAVs greatly depends on the accuracy and effectiveness of the pre-established safety rules and algorithms that govern their decision-making process. In this context, we have proposed a new traffic safety rule that connects key parameters such as **Time-To-Collision (TTC)**, **Space Headway (SHW)**, and **Shockwave (SWV)** speed to analyze changes in TCTs and the likelihood of traffic conflicts. Our findings have important implications for developing robust and efficient safety protocols for CAVs, which can help ensure their safe and widespread adoption. To demonstrate the real-life applicability of the proposed rule, we conducted a case study by simulating a real-life dataset and monitoring the extracted TTC, SHW, and SWV for consecutive vehicles in the same platoon. The integration of Mathematica and SUMO allows for an efficient adaptive traffic management system, dynamically adjusting vehicle speed based on real-time conditions to improve traffic flow and reduce conflicts. By implementing the traffic safety rule on the provided traffic dataset for the SR528 highway, our objective was accomplished by attaining elevated SHW, TTC, and SWV values, reaching a remarkable increase of 290.8%. The implementation of this traffic rule resulted in fewer traffic conflicts, reduced shockwaves, and minimized their negative impacts. The case study illustrates the effectiveness of this safety traffic rule. Additionally, these rule-based tools can be integrated to apply the same approach to other real-world datasets, enabling the extraction, analysis, and control of vehicle dynamics when a traffic safety rule violation is identified. Improving the research could involve integrating **Satisfiability Modulo Theories (SMT)** solvers with SUMO. This integration could enhance the scalability of the approach and provide a flexible means for creating more dependable adaptive traffic management systems. The traffic safety regulations explored in this project are centered on the car-following models. However, there is an opportunity to investigate alternative traffic behaviors such as lane changing and weaving and diverse road facilities such as roundabouts, where side-swipe conflicts may be more prevalent.

***Future Work.***

— Perception is a foundational component of autonomous vehicle technology, combining computer vision techniques with advanced algorithms to enable vehicles to "see" and understand their environment. Ongoing research in this field, such as References [8, 9] aims to enhance the accuracy, reliability, and safety of autonomous driving systems, making them more adaptable to real-world complexities. Inspired by the work of Reference [12], we aim to investigate the integration of computer vision and real-time decision making for the AV to navigate safely and efficiently.
— In our work, we primarily focused on longitudinal speed updates. However, incorporating lateral vehicle speed, as proposed in Reference [13], could extend this study to account for lane changes and offer valuable insights into these behaviors, ultimately enhancing the decision-making process.

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