

Statistical Model Checking for the Analysis of Attacks in Connected Autonomous Vehicles

Cinzia Bernardeschi*, Adriano Fagiolini[†], Dario Pagani*, Christian Quadri[‡]

* Department of Information Engineering, University of Pisa, 56100 Pisa, Italy

Email: cinzia.bernardeschi@unipi.it, dario.pagani@ing.unipi.it

[†] Department of Engineering, University of Palermo, 90133 Palermo, Italy

Email: adriano.fagiolini@unipa.it

[‡] Computer Science Department, University of Milan, 20122 Milan, Italy

Email: christian.quadri@unimi.it

Abstract—This paper proposes an approach for the analysis of the effects of attacks in connected autonomous vehicles by simulated attack injection and statistical model checking technique. The vehicles, together with the co-ordination algorithm among vehicles and the attacks are formalized using hybrid automata in UPPAAL framework. Then, the statistical model checker, UPPAAL-SMC, allows to study the resilience of the system to attacks across a range of circumstances and uncertainties. The approach is applied to a platoon of vehicles, and properties of the system under attack in case of various driver patterns of the platoon's leader and parameters of a data alteration attack are analyzed.

Index Terms—Statistical Model Checking, Autonomous Vehicles, Cybersecurity, UPPAAL, Platoon Resilience

I. INTRODUCTION

Cybersecurity is an important topic for connected autonomous vehicles, since they are highly computerized and connected to the network, thus providing a wide range of access points for a potential attacker, who could gain full control over the vehicle and turn off all safety measures installed on it [1]. Many attack types have been developed and tested on a vehicle, proving that the considered vulnerabilities could actually be exploited by a potential attacker.

Platooning [2] is a driving strategy where multiple vehicles travel closely together in a coordinated group, enhancing road safety, lowering emissions, and reducing driver workload. The main goal of a platoon system is to maintain a predefined inter-vehicle distance determined by a spacing policy, and to guarantee the string stability, i.e. to avoid perturbation propagating along the vehicles' string. These two objectives are obtained through vehicle cooperation. Traditionally, platoon vehicles cooperation is performed using vehicle to vehicle (V2V) communication, exploiting IEEE 802.11p standard. The advent of 5G has enabled centralized approaches that combine cellular communications and multi-access edge computing (MEC), as proposed in [3].

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UPPAAL [4] is an integrated tool environment for modeling, validation and verification of real-time systems modeled as networks of *timed automata* [5]. A timed automaton consists of a set of states (locations) and transitions, and a set of real-valued variables for measuring time between transitions, named Clocks. Invariants can be added to locations to specify timing constraints on leaving the locations.

Connected vehicles are complex CPSs which communicate through a network and they are generally characterized by unpredictability and variability.

From the point of view of modeling, in UPPAAL physical quantities and their derivatives can be modeled with clocks; and for what concerns the analysis of system's properties, Statistical Model Checking (SMC) can be used [6]. SMC encompasses a range of techniques that monitor several executions of the system with respect to specific property, leveraging statistical methods to estimate the overall correctness of the model with a specified level of confidence. For example, in [7] this approach is applied in the field of power electronics, to gauge the performance of electrical converters; in [8] SMC is used to validate the safety properties of an autonomous vehicle controller for switching lane on a motorway; in [9] this approach has been used to probabilistically validate the safety properties of joining and leaving a vehicle platoon; and [10] shows the validation of a Bayesian perception framework, built to track the spatial occupancy, in detecting a potential collision while approaching a crossroad.

Particularly, in the field of cybersecurity, in [11] SMC was used to study the probability of a property of an attack in a web API, as traditional model checking cannot realistically explore all states of the system; the work is centered around software systems. The work [12] presents a methodology based on stochastic timed automata to model a system and attack-fault trees to model attacks, to evaluate the risk, it was applied to a steam boiler system used in industry.

In this work, we present a novel approach to analyse security of connected autonomous vehicles using model-based attack injection and SMC. The system, with its control laws and physics, is modeled as a timed automaton in UPPAAL; the system model is extended with the injection of attacks; and the effects of the attacks on the system safety are analysed

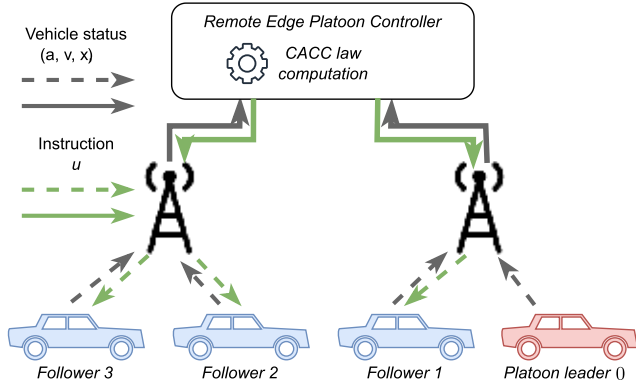


Figure 1: Edge-based platoon control schema

by using UPPAAL SMC probabilistic queries. In particular, the approach exploits UPPAAL SMC's ability to change a clock rate through the Lagrangian derivative notation to model physical quantities and attacks through them. For instance, a simple physical system can be model as $x' = v, v' = a$ where x and v are defined as UPPAAL clocks.

We show the application to a platoon of vehicles, in case of data alteration attack to state parameters of the vehicles.

Numerous modeling approaches for attacks on connected autonomous vehicles have been proposed [13]. While these methods provide structured analyses of attack surfaces and scenarios, they often lack the capability to capture the stochastic nature of both vehicular dynamics and attacker behavior in realistic operating conditions. SMC addresses this gap by enabling probabilistic analysis over a range of uncertainties.

The paper is structured as follows: Section II illustrates basic concepts used in this work, Section III shows the network of timed automata modeling the platoon and attacks, Section IV uses UPPAAL to simulate the behavior of the platoon, Section V uses UPPAAL SMC's probabilistic queries to analyze properties of the platoon and Section VI includes a discussion and conclusions.

II. BACKGROUND

This section briefly introduces the platooning application and the formal modelling framework UPPAAL through a simple example.

A. Platooning

We consider a generic platoon remotely managed by an edge platoon controller (MEC approach), as described in [3] and reported in Fig. 1. There are four vehicles moving along one axis forming a platoon, one leader's driver and three follower vehicles. Each car is indexed from 0 to 3, starting from the leader with 0. In our model, we use the Cooperative Adaptive Cruise Control (CACC) [14] for the co-ordination of the platoon.

In particular, each vehicle i is characterized by four scalar values $(u, a, v, x)_i$, these are the state variables of the vehicle. The first value u_i is the car's input value and represents the

vehicle's desired acceleration: for the leader (value u_0), it is a known function part of the problem's hypothesis; whereas for the other cars it's the output of the control system. The other values are the current output values and represent, for each vehicle, respectively, the current acceleration a_i , the velocity v_i and the position x_i .

Each vehicle sends the value of its state variables to the remote controller hosted on the edge server through the mobile network. The controller collects the status of all cars, after which the CACC control law is applied to compute the desired acceleration of each follower. The desired accelerations are then sent back to the cars.

Let D be the desired distance between car i and the car in front $i - 1$. Formally, the instruction for the i -th vehicle, with $i > 0$, is given by the formula

$$u_i = \alpha_1 a_{i-1} + \alpha_2 a_0 + \alpha_3 (v_i - v_{i-1}) + \alpha_4 (v_i - v_0) + \alpha_5 (D - d_i), \quad (1)$$

where d_i is the distance to the vehicle in front ($d_i = x_{i-1} - x_i - l$), with l the length of the car), and α_i are control gain parameters. We assume in our case-study, $\alpha = (0.5, 0.5, -0.3, -0.1, -0.04)$.

The desired acceleration (also named reference acceleration) for vehicle i , depends on the acceleration of the vehicle in front; the acceleration of the leader; the difference of velocity between the vehicle and the vehicle in front; the difference of velocity between the vehicle and the leader; the gap between the desired distance D and the distance to the vehicle in front. The overall behavior of the platoon is imposed by u_0 , the acceleration command given to the leader, which is a signal dependent only on time.

B. Uppaal SMC

Consider the simple system in Fig. 2, composed of two cars, one following the other. The leader car (Driver) moves according to a given driving scenario and imposes the acceleration on the follower car (Car).

Each car is represented by an automaton. The acceleration imposed on Car is defined by a global variable a , set by the Driver. The clock variable t , defines interleaving time between transitions. Fig. 2 (a) models the Driver. **INIT** is the initial location. The driver's behavior is modeled as follows. The first transition is enabled and set the acceleration to $a = 1 \frac{m}{s^2}$. The

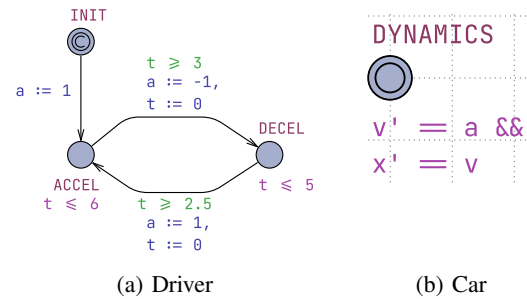


Figure 2: A simple UPPAAL system

Table I: Global clocks and variables

Name	Type	Description
t_sim	clock	Time t elapsed
a_p[N_CARS]	clock[]	Cars' real accelerations
v_p[N_CARS]	clock[]	Cars' real velocity
x_p[N_CARS]	clock[]	Cars' real positions
a[N_CARS]	clock[]	accelerations sent to CACC
v[N_CARS]	clock[]	speeds sent to CACC
x[N_CARS]	clock[]	positions sent to CACC
a_n[N_CARS]	double[]	CACC input after net. delays
v_n[N_CARS]	double[]	CACC input after net. delays
x_n[N_CARS]	double[]	CACC input after net. delays
u[N_CARS]	double[]	Desired accel. sent to cars
u_n[N_CARS]	double[]	Desired accel. after net. delay
cacc	broadcast chan	CACC synchronization
crashed[N_CARS]	bool[]	Crashed cars
A	double[]	Attack amplitude

location **INIT** is marked with a **C** that stands for *committed*, time is not allowed to pass when a process is in a committed location. In the example, it forces the automaton to transition to state **ACCEL** and thus assigns $a := 1$ immediately. Then, invariant $t \leq 6$ assigned to location **ACCEL** and guard $t \geq 3$ of the transition exiting the location guarantees that the transition is executed in the time range $[3, 6]$. The execution of the transition assigns a new value to the global variable a and the clock t is reset to 0. A similar behaviour is exhibited when the system is in location **DECEL**. The Driver alternates an acceleration period of length $T_A \in [3, 6]$ with $a = 1 \frac{m}{s^2}$ and a deceleration period of length $T_D \in [2.5, 5]$ with $a = -1 \frac{m}{s^2}$.

Fig. 2 (b) shows the Car automaton. It consists in a single location **DYNAMICS**. Speed and position are represented by two clocks, x and v , that model the physics via the Lagrangian derivative notation. The location is assigned the following invariants: "the derivative of the velocity is always equal to the acceleration" and "the derivative of the position is always equal to the velocity". During the system's execution, all clocks are updated accordingly, in particular the car's automaton updates the velocity and position of the car.

Suppose we want to compute the probability of the velocity will exceed a given threshold within a specified time range: $\exists v$ in the period $[55, 60]$ seconds such that $v > 10 \frac{m}{s}$. A possible UPPAAL SMC query formulation is $\text{Pr}[t_sim \leq 60] (<> t_sim \geq 55 \ \&\& \ car.v > 10)$, where $\text{Pr}[t_sim \leq 60]$ selects simulation traces in the first 60s, and $(<> t_sim \geq 55 \ \&\& \ car.v > 10)$ selects paths in which there exists a state satisfying the condition on simulation time ≥ 55 and car velocity > 10 . Such a query yields an estimated probability of 74 % with confidence interval of 95 %. The desired confidence interval is a parameter of the program. For more information on UPPAAL, the reader can refer to [15].

III. MODELING

In this section, we describe the timed automata for the platoon in Fig. 1 and how attacks are modeled.

A. Vehicle model

A summary of global clocks and variables is shown in Table I. The system has one global clock t_sim that represents the time t elapsed from the beginning of a simulation, it is never stopped or changed.

The input/output values of the cars composing the platoon are modeled as UPPAAL's clocks. Let $\hat{a}_i, \hat{v}_i, \hat{x}_i$ the real physical quantities for the i -th car; these values are necessary to model the physical evolution of the cars.

The input values u_i of the various cars are modeled as an array of doubles $u[N_CARS]$, $u_n[N_CARS]$, with N_CARS the number of cars.

For the output values, there are six clocks for each car: $a_p[i]$, $v_p[i]$, $x_p[i]$, $a[i]$, $v[i]$ and $x[i]$; where the $_p$ clocks represent the real physical quantities, while the other clocks are used to model attacks in the platoon. They represent the value actually sent by the car to the remote Controller in case of data alteration attack.

To synchronize the various CACC units the *broadcast channel* **cacc** action is used.

The i -th elements of the boolean vector **crashed**[N_CARS] are set to true after the i -th car has either rear-ended or has been rear-ended.

The global variable A represents the data alteration attack with amplitude A .

B. Attack model

We consider attacks that adds spurious signals to data sent by the car to the controller. Attacks that affect data sent back by the controller to cars can be modeled in a similar way.

Assume t_A to be the time at which the attack starts. Let us consider the case of a low-frequency sinusoidal attack of 1 Hz of frequency and of amplitude A , applied to real acceleration value $\hat{a}(t)$ as shown in (2) — the coefficient $\frac{2\pi}{10}$ is the frequency expressed in radians per second. In the example, we assume the acceleration, velocity and position values are modified coherently, assuring that the relation $x' = v, v' = a$ holds true. Additionally, for the velocity, a small bias $\frac{5}{\pi}A$ is introduced in (3). The problem is made interesting by the signal's construction, which is designed to be difficult for an external observer to detect.

The data are altered, when $t \geq t_A$, as shown in (2), (3), (4).

$$a(t) = \hat{a}(t) + A \sin\left(\frac{2\pi}{10}t\right) \quad (2)$$

$$v(t) = \hat{v}(t) - \frac{5}{\pi}A \cos\left(\frac{2\pi}{10}t\right) + \frac{5}{\pi}A \quad (3)$$

$$x(t) = \hat{x}(t) - \frac{25}{\pi^2}A \sin\left(\frac{2\pi}{10}t\right) + \frac{5}{\pi}At. \quad (4)$$

If car 1 is sending spurious data to the Controller, then the CACC of car 2 sees, for example, an erroneous distance $d_2(t) = x_2(t) - x_1(t) - l$.

C. System model

The system is modeled by a network of timed automata.

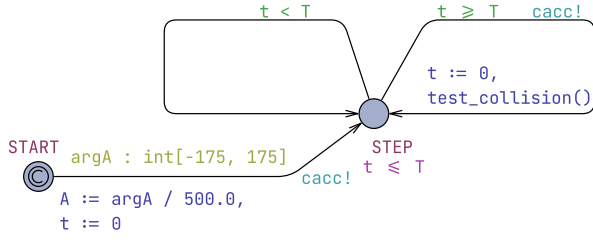


Figure 3: The Simulation automaton

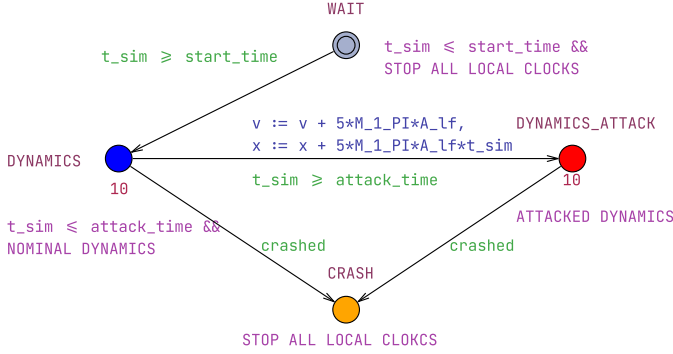


Figure 4: The CarDynamics template automaton

1) *Simulation automaton*: The Simulation automaton, shown in Fig. 3, is used to update, every $T = 0.01s$, the simulation's global variables that track collisions between vehicles and to synchronize the CACC's computation; the former is done by calling the `test_collision()` function and the latter by emitting a `cacc!` broadcast synchronization. Every simulation step, the instances of the CACC synchronize on the broadcast channel by executing `cacc?`, see the CACC automaton in Fig. 5. Concerning the attack, the Simulation automaton sets a value to A . The committed initial location **START** is connected to location **STEP** via a transition that sets the value of A by drawing it from a discrete uniform distribution ($ArgA : \text{int} [-175, 175]$).

The Simulation's **STEP** location has a looping edge with guard $t \geq T$, that ensures the synchronization with the controller is executed exactly every T seconds.

2) *CarDynamics automaton*: The template CarDynamics, as shown in Fig. 4, models the car's dynamics. Each template instance models a car, one for the leader and three for the followers. There are four states:

a) *Wait*: The **WAIT** location represents the car waiting for its time to start moving after `start_time` seconds. **STOP ALL LOCAL CLOCKS** is the state invariant in which all clocks modeling the physics are stopped by imposing their prime derivatives to zero, that is $x' == 0 \ \&\& \ v' == 0 \ \&\& \text{etc.}$

b) *Dynamics*: The **DYNAMICS** location models the time evolution of the vehicle given the input signal u . The state invariant **NOMINAL DYNAMICS** models the physics of the running car (not reported for brevity).

Being in location **DYNAMICS**, if $t_A = +\infty$ then no attack takes place as the guard $t_{sim} \geq \text{attack_time}$ of the transition

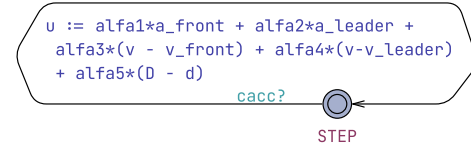


Figure 5: The CACC automaton

from location **DYNAMICS** to **DYNAMICS_ATTACK** is always false. When an attack starts, such transition updates clocks x and v to set the conditions required by (3) and (4).

c) *Dynamics attack*: The **DYNAMICS_ATTACK** location is the same as the former but with the attack. **ATTACK DYNAMICS** is the state invariant in which the clock rate of the sensors' values are altered according to (2),(3), (4). The state invariants are not reported in the figure for brevity.

d) *Crash*: The **CRASH** location represents a crash with another vehicle **STOP ALL LOCAL CLOCKS** is the state invariant and it is the same as the **WAIT**'s.

When a collision involving the car is detected, the guard `crashed` is satisfied, eventually causing a transition to the state **CRASH**; the locations modeling the dynamics (**DYNAMICS** or **DYNAMICS_ATTACK**) of the vehicle have the exponential rate λ set to **10**, that is in the event of a crash it will transition to the **CRASH** location after an average time of $\lambda^{-1} = 100 \text{ ms}$. The local variable `crashed` of car i is a reference to the global variable `crashed[i]`.

3) *Driver automaton*: The automaton Driver models the driving pattern of the leader. This automaton generates the u_0 acceleration signal fed to the leader car. Three different operational modes, chosen stochastically with equiprobability $\frac{1}{3}$. The operational modes are:

- 1) the driver drives up to speed with constant acceleration
- 2) the driver drives up to speed with linear acceleration
- 3) the driver alternates periods of constant acceleration, no acceleration and constant deceleration

The parameters of the accelerations are set randomly at the start. For brevity's sake, we omitted this automaton. An example of simple Driver automaton is in Fig. 2(a).

4) *CACC automaton*: The controller at the edge is modeled by the CACC template: this automaton implements the CACC laws, for a vehicle. As shown in Fig. 5, all CACC instances are tied together by a `cacc?` broadcast synchronization channel. The transition is executed upon synchronization on the `cacc!` action from the Simulation automaton.

5) *UPLINK and DOWNLINK automata*: The communication network is modeled as follows:

- **UPLINK** template: this automaton models the transmission delay when sending a message from car to CACC
- **DOWNLINK** template: this automaton models the transmission delay when sending a message from CACC to car

The transmission delay is from an exponential distribution and models an average delay of 33 ms. For brevity's sake, we omitted the timed automaton UPLINK and DOWNLINK.

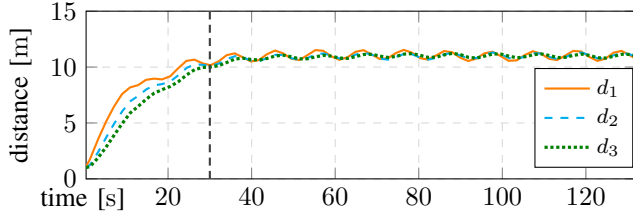


Figure 6: Distances between cars as time passes (no attack)

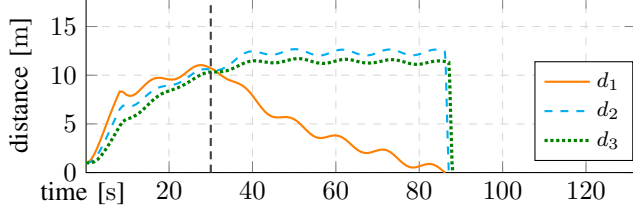


Figure 7: Distances between cars as time passes with $A < 0$

IV. UPPAAL SIMULATION

In this section we use UPPAAL's query `simulate` to simulate the behavior of the platoon.

We show three possible behaviors of the platoon, plotting the distance d_i kept between pairs of consecutive cars. We consider a base case in which no attack takes place (that is $t_A = +\infty$ for all cars), and two cases with attack at $t_A = 30$ s on car 1 with $A = \pm 0.08$.

The results of the three simulations are shown in Fig. 6, 7, 8. In the first 20 to 25 s the cars start moving and get up to speed. All cars start with $d_i(0) = 1$ m and the desired distance is set to $D = 11$ m. In the nominal case (no attack), all d_i converge to 11 m as expected, see Fig. 6. With $A = -0.08$ (Fig. 7) we can see how car 1, shown as the orange solid line in the figure, gets closer and closer to the leader as d_1 approaches 0 m, until it rear-ends it. Since we are not modeling the crash physics and assuming the two vehicles halt immediately, the behavior of car 2 and 3 after the crash is not meaningful; in this scenario the control law is not able to stop the car 2 and 3, causing a pile-up.

Interestingly, with $A = +0.08$ (Fig. 8) we do not observe any crash; however car 1, shown as the orange solid line in the figure, tends to get further and further away from the leader, causing a loss in efficiency.

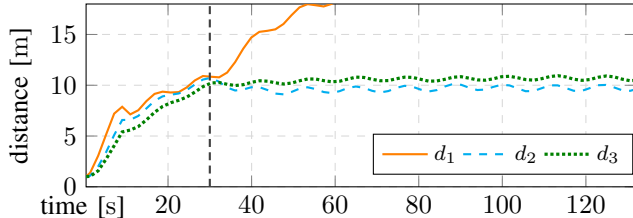


Figure 8: Distances between cars as time passes with $A > 0$

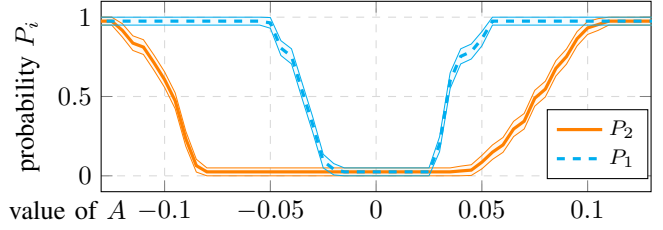


Figure 9: Probability of $\varepsilon_1 \geq 15\%$ (P_1) and $\varepsilon_2 \geq 15\%$ (P_2) within the first 10 seconds over A

V. UPPAAL PROBABILISTIC QUERIES

In this section we make use of UPPAAL SMC's queries. As the inter-vehicular distance is the main value used to control the follower cars, CACC tries to reduce the error between the actual and the desired distance, we use it as the primary metric to gauge the behavior of the system under attack.

A. For attack detection

Each car in the platoon tries to maintain a gap d to the vehicle in front as close as possible to desired distance D . During an attack such value might change quite drastically in a narrow window of time, making certain methods of detection unfeasible. We want to gauge the probability of the *error* being $\varepsilon_i = |d_i - D| > 15\%$ during the first 10 s from the begin of attack, the lower the value ε_i the more time a hypothetical detector may have to properly identify the threat.

Assume the attack takes place on car 1 and the attack starts at $t_A = 30$ s. To check if the distance remains within margin between car 0 and car 1, and between car 1 and 2; the queries can be formulated as :

- $\text{Pr}[t_{\text{sim}} \leq 40] (\langle t_{\text{sim}} \rangle = 30 \ \&\& \text{fabs}((x_p[0] - x_p[1] - 4)/11 - 1) > 0.15)$
- $\text{Pr}[t_{\text{sim}} \leq 40] (\langle t_{\text{sim}} \rangle = 30 \ \&\& \text{fabs}((x_p[1] - x_p[2] - 4)/11 - 1) > 0.15)$

where each vehicle has length 4 m.

Consider the first query, it estimates the probability of $\varepsilon_1 > 15\%$ at least once in the interval $[t_A, t_A + 10\text{s}]$. The time interval is implemented by setting an upper bound of $t_{\text{sim}} \leq 40$ and by putting $t_{\text{sim}} \geq 30$ in conjunction with the formula to verify. The *at least once* is implemented by using the operator $\langle \rangle$. The `fabs()` is the function to compute the *floating-point* absolute value.

We parametrized the value of A instead of stochastically assigning it at start-up. We varied the value of A and ran the queries. The results are shown in Fig. 9, the values of $P_i = P(\varepsilon_i \geq 0.15 | 30 \leq t \leq 40)$ are plotted against A , the confidence interval was set to 95%.

B. For safety

Let us now consider the problem of the safety of the overall platoon. That is, what's the probability, given an attack of amplitude A , of *not* having a significant effect on the distance between *all* cars in the first 10 s from the begin of the attack.

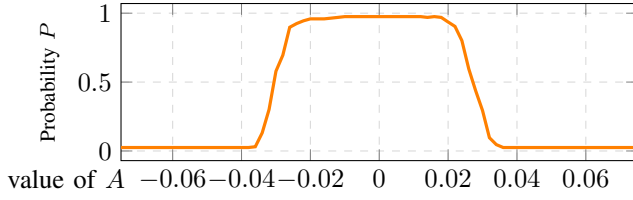


Figure 10: Probability of keeping the correct distance

This is the complementary problem of the one exposed in the previous section and can be formulated as:

- $\text{Pr}[t_{\text{sim}} \leq 40] ([t_{\text{sim}} \geq 30 \text{ imply forall } (i : \text{int}[1, 3]) \text{ fabs}((x_p[i-1] - x_p[i] - 4)/11 - 1) < 0.15])$

The query thus formulated is quite similar to the one described in the previous section. In particular, it computes the probability of $\forall i \ \varepsilon_i < 0.15$ in the first ten seconds of an attack on car 1 with $t_A = 30$ s. The `imply` operators implements the logical implication and it is used to check the condition on the error only when the antecedent $t \geq 30$ s is true; when the antecedent is false the expression already evaluates to true. The operator `[]` means the condition must hold true continuously until the upper bound on t_{sim} is reached. The query is equivalent to state:

$$P(\forall t \leq 40\text{s}, \quad t \geq 30\text{s} \implies \forall i \ \varepsilon_i < 0.15).$$

We ran the query multiple times varying A in the same way as we did in the previous section. The results are shown in Fig. 10, with confidence interval of 95%. We can see how very small values of A do not affect the safety.

The results align with those from the previous section, a conclusion that could not have been assumed a priori, given the uncertainty regarding the statistical independence of the operands in the conjunction $\forall i \ \varepsilon_i < 0.15$.

VI. DISCUSSION AND CONCLUSIONS

This work demonstrates UPPAAL’s effectiveness in modeling and analysis of attacks in cyber-physical systems through: automata integrating continuous dynamics (vehicle kinematics) with discrete events (network delays and time-discrete controllers); automata with stochastic variables capable of modeling a wide range of behaviors; and probabilistic analysis of emergent behaviors via statistical model checking.

The results show several critical insights into the effects of attacks in the platoon. The statistical model checking approach proved particularly effective for evaluating safety properties in cyber-physical systems. By formulating safety requirements as probabilistic queries, we can quantitatively assess certain behaviors of a system. Our probabilistic analysis provides a foundation for intrusion detection systems. The probability $P(\varepsilon_i \geq 0.15)$ within 10-second windows serves as an effective metric for real-time anomaly detection.

One limitation with our approach is that, when modeling complex systems and studying the effect of an attack whose probability of occurring is really small, the event might not

appear in any trace or be irrelevant in the final probability computation. To appreciate its effect one should increase the UPPAAL SMC’s confidence parameters that might result in the necessity to accumulate a large number of traces, thus making it computationally expensive.

Our attack model focuses on steady-state sinusoidal perturbations. As further work, it might be interesting to consider more sophisticated time-varying attack patterns that could be employed by attackers. Moreover, we intend to explore a more general methodology to perform risk-assessment of cyberphysical systems under attack, using as metric the damage severity and its occurrence probability.

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