Resilience-by-design in Adaptive Multi-agent Traffic Control Systems

RANWA AL MALLAH, Royal Military College of Canada, Canada  
TALAL HALABI, Laval University, Canada  
BILAL FAROOQ, Toronto Metropolitan University, Canada

Connected and Autonomous Vehicles (CAVs) with their evolving data gathering capabilities will play a significant role in road safety and efficiency applications supported by Intelligent Transport Systems (ITSs), such as Traffic Signal Control (TSC) for urban traffic congestion management. However, their involvement will expand the space of security vulnerabilities and create larger threat vectors. In this article, we perform the first detailed security analysis and implementation of a new cyber-physical attack category carried out by the network of CAVs against Adaptive Multi-Agent Traffic Signal Control (AMATSC), namely, coordinated Sybil attacks, where vehicles with forged or fake identities try to alter the data collected by the AMATSC algorithms to sabotage their decisions. Consequently, a novel, game-theoretic mitigation approach at the application layer is proposed to minimize the impact of such sophisticated data corruption attacks. The devised minimax game model enables the AMATSC algorithm to generate optimal decisions under a suspected attack, improving its resilience. Extensive experimentation is performed on a traffic dataset provided by the city of Montréal under real-world intersection settings to evaluate the attack impact. Our results improved time loss on attacked intersections by approximately 48.9%. Substantial benefits can be gained from the mitigation, yielding more robust adaptive control of traffic across networked intersections.

CCS Concepts: • Security and privacy → Distributed systems security; Mobile and wireless security;

Additional Key Words and Phrases: Intelligent transportation systems, adaptive multi-agent traffic signal control, connected and autonomous vehicles, coordinated Sybil attack, data corruption attacks, game theory, attack mitigation, resilience-by-design

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1 INTRODUCTION

Intelligent Transportation Systems (ITSs) play a vital role in the development of smart cities by enabling a plethora of road safety and efficiency applications such as optimized traffic management and collision avoidance. Adaptive Multi-Agent Traffic Signal Control (AMATSC) is one of the
aspects that make these systems intelligent by increasing the responsiveness of traffic signals to traffic demands. The cost of traffic congestion in wasted fuel and lost productivity ranges between 1.5 and 5 billion CAD per year in major Canadian cities [5]. By collecting and evaluating traffic data in real time, AMATSC technologies try to optimize signal timings to reduce urban congestion and ensure reliable vehicle travel time.

AMATSC is deployed extensively in North America, Australia, and Europe. For instance, the Sydney Coordinated Adaptive Traffic System (SCATS), Split Cycle Offset Optimization Technique (SCOOT), RapidFlow, Rhythm engineering, InSync, Urban Traffic OPTimisation by Integrated Automation (UTOPIA), Adaptive Control Software (ACS Lite), and Real-time Hierarchical Optimized Distributed and Effective System (RHODES) represent widely known deployments [24]. They are in use in Pittsburgh, Pennsylvania; on Boudreau Road in the City of St. Albert, Alberta, Canada; and in the suburb of Toronto, the Holton region, and downtown Toronto. By the end of 2021, the size of the deployment is expected to grow to hundreds more in operation in downtown Toronto, Montreal, and many other cities around the world [23].

The network of Connected and Autonomous Vehicles (CAVs) will be increasingly involved in AMATSC operations, where valuable traffic parameters that are often difficult to obtain from the static transportation infrastructure are transmitted through the vehicles’ On Board Units (OBUs) to the infrastructure’s Road Side Units (RSUs) and integrated into the AMATSC algorithms to optimize their signal timing decisions. However, the reliance on CAV increases the vulnerability of ITS to cyberattacks [3] due to the high connectivity involved. AMATSC may be implemented and managed by the Traffic Management Center (TMC). Microscopic and macroscopic traffic variables collected at the RSUs and transmitted to the TMC are critical to AMATSC algorithms for optimal decision making. However, they may be misleadingly altered in the presence of malicious vehicles trying to launch data corruption attacks, such as Sybil. Basically, Sybil vehicles are non-existing vehicles controlled by a malicious entity and claiming fake or forged identities to participate in ITS operations, sabotaging their reliability and performance.

The communication protocols used by traffic cabinets lack effective data encryption and authentication mechanisms [28]. Consequently, the Sybil attack exploits the lack of security countermeasures on traffic controllers and sensors to expose the vulnerabilities of AMATSC algorithms. Sybil attacks in Peer-to-Peer (P2P) networks have been well studied in the literature, and many solutions were designed to identify and isolate Sybil nodes within these networks [17]. However, Sybil attack prevention and detection in wireless networks is not straightforward when the attack becomes complex. Hence, it is imperative to equally focus on designing effective mitigation solutions to preserve the resilience of traffic applications when the primary lines of defense are compromised.

In this article, we investigate theoretically and experimentally the potential and impact of a yet-unexplored threat model on AMATSC systems, namely the coordinated Sybil attack. In such an attack, the Sybil vehicles are deployed to alter the data collected by the AMATSC algorithms on networked intersections by optimally targeting the controllers involved in signal timing decisions. The motivation behind our security analysis is to stress the need for these algorithms to be attack aware. This could be achieved through the integration of mitigation strategies into the AMATSC decision making as a resilience layer against sophisticated attacks.

Therefore, we devise a non-cooperative minimax game model to formalize the interactions between the attacker and the AMATSC system, then solve the game to generate the optimal attack and defense strategies. On one hand, the coordinated Sybil attack consists in playing a mixed strategy drawn from the attack action space and is reflected by the adaptive deployment of Sybil vehicles on networked road junctions to maximize their traffic flows. On the other hand, the AMATSC algorithm adopts a mixed strategy of attack mitigation actions that consists of applying
a weighted integration of the data collected by the network of traffic controllers in an attempt to optimize signal timing decisions under attack.

The contributions of this article are summarized as follows:

- We perform the first detailed security analysis of a highly realistic cyber-physical threat model carried out by a network of CAVs on AMATSC systems. We experimentally demonstrate its effectiveness and measure its impact on traffic control decisions using a real traffic dataset provided by the city of Montréal.
- We propose a novel, application-layer Sybil attack mitigation approach based on a minimax game model. Unlike other mitigation solutions that focus on reducing the impact of the attack following its detection, our approach integrates a resilient response to attacks into the generation of decisions. This “by design” solution can be considered as a fail-safe of the attack detection phase and can be deployed as the default operational strategy under susceptible adversarial settings where critical traffic data might be maliciously corrupted.
- We implement the mitigation approach onto an existing Multi-Agent Reinforcement Learning (MARL)-based AMATSC algorithm and evaluate its performance under various scenarios. The results show that attack mitigation substantially reduces vehicle delays and yields optimal control of traffic across networked intersections under attack.

The remainder of the article is organized as follows. Section 2 presents important background concepts and discusses the related literature. Section 3 describes the new threat model and its impact. Section 4 lays out the proposed mitigation approach. The implementation details are presented in Section 5. Section 6 discusses the experimental setup and analyzes the results. Finally, Section 8 concludes the article.

2 BACKGROUND AND LITERATURE REVIEW

The dependability and safety of ITSs rely on their security against cyber and cyber-physical attacks, which target the perception layer of the architecture and propagate their impact to the application layer. Traffic Signal Control (TSC) has evolved from standalone hardware devices running static schedules into complex, wireless connected systems, which exposed them to a variety of cyberthreats [24]. Signal controllers are usually placed in metal cabinets by the roadside and used to generate signal timing plans by following different approaches: fixed-time, actuated and semi-actuated, and adaptive. In particular, adaptive TSC has proven to increase transportation productivity and reduce gas emissions.

2.1 Adaptive Multi-agent TSC

AMATSC emerged as a new ITS paradigm, persuaded by the idea that traffic light timing plans should be fully adaptive in coping with actual traffic demand (intersections’ traffic load). Rather than monitoring the states of isolated intersections, AMATSC observes the state of networked intersections to produce signal timing decisions based on the global state of the road network [8]. To achieve this, the local controllers at every intersection communicate with each other directly or via the TMC, as depicted in the architecture of Figure 1.

The potential for performance improvements in AMATSC driven by Reinforcement Learning (RL) when compared to conventional approaches is very promising [19]. When developing MARL-based AMATSC models, the literature draws on different parameters for state and reward definitions within the Markov game played among the agents [2]. For instance, queue length is often used to define the environment state. Some studies propose a vehicle-based state definition using the expected total waiting time of a vehicle before reaching its destination. More generally, delay-based approaches exploit a combination of parameters such as the queue length and the
traffic flow rate, or the queue length and the time elapsed since the previous signal. Similarly, a variety of objectives have been considered when estimating the reward function such as the average trip time, average junction waiting time, and junction throughput/flow rate.

### 2.2 Security of AMATSC

AMATSC algorithms manage the signal timings of multiple networked intersections. CAV-based traffic control is the future of AMATSC and will greatly improve its efficiency by allowing the vehicles to transmit relevant information to urban traffic scheduling algorithms. However, this increased connectivity aggravates the vulnerability of AMATSC algorithms to falsified data and erroneous measurements, especially if they are not designed with the intrinsic ability to detect or ignore these measurements during decision making. For instance, Figure 2 shows how a MARL-based AMATSC can be targeted by data corruption attacks that may sabotage the environment conditions on which the traffic control agents rely to derive their optimal signal timing policy.

Ghena et al. [12] investigated the security of an AMATSC system currently deployed in the United States and discovered a number of serious security flaws, which mainly exist due to systemic design failures and may be exploited to create attacks that gain control of the system and cause service disruption. Chen et al. [4] conducted a detailed security analysis of CAV-based transportation and studied the impact of data spoofing attacks performed by the vehicles. They found that the current traffic control algorithm design choices are highly vulnerable to such attacks from even a single vehicle. Yen et al. [27] also studied the performance of different AMATSC scheduling algorithms when they are under attack. Feng et al. [10] focused on attacking actuated and adaptive control systems by sending falsified data to increase traffic delay. Although these attacks are still relatively simple, they attempt to emphasize the vulnerability of scheduling algorithms.

Laszka et al. [16] proposed an approach for detecting and mitigating the attacks on traffic signals by optimizing the detector’s configuration, which implies that the mitigation process is based on the success of the detection phase. Our work underlines the importance of deploying the mitigation procedure at the application layer during the design phase without relying on the precedent line of defense, where the AMATSC algorithm integrates an intrinsic form of smart resilience when processing the data collected from the physical world independently of intrusion detection functions.
2.3 Resilience-by-design

To the best of our knowledge, the robustness of the parameters used for state and reward definitions in the face of cyberattacks against the ITS remains questionable. The attack carried out in this article proves that the intrinsic parameters used by the traffic control logic are extremely vulnerable to corruption and require serious investigation. Thus, we stress the need to develop resilient-by-design AMATSC algorithms as part of a defense-in-depth security approach, where an additional mitigation layer is deployed on top of the application layer.

The idea of security-by-design for cyber-physical systems has been introduced very recently [11]. In principle, it allows to incorporate security measures at the system design phase following careful specification of security requirements. This article largely contributes to this area of research, which is still in its infancy, by emphasizing the need to equally introduce security and resilience-by-design at the application layer of the cyber-physical architecture. This is a crucial line of defense, especially against intelligent attacks and advanced persistent threats that will most likely bypass detection.

Game theory provides a high-level mathematical language, generally perceived as effective in modeling the conflicted interactions between attackers and defenders in modern computer systems and optimizing their decisions. Several games have been proposed to detect the attacks on ITS and address traffic prediction and decision-making issues [22]. In such games, usually non-cooperative, players aim at maximizing their own payoffs and minimizing the payoffs of their opponents [1]. The attacker’s payoff can be modeled either as the gain from launching the attack on the ITS or as the impact of the attack on system performance. In this article, we leverage the power of game theory to anticipate the malicious activities that target ATSC and prepare the controllers to respond proactively and in an optimized fashion.

2.4 Sybil Attacks in the CAV Environment

Sybil attacks were first introduced by Douceur [6] in P2P networks: if a single faulty or malicious entity can present multiple identities, it can control a substantial fraction of the system, thus representing a security threat. Many Sybil attack detection techniques were proposed [14, 26], but most of them present serious shortcomings in practicality and detection accuracy, especially if faced with sophisticated attacks. In fact, without a centralized trusted authority, it is impossible to completely detect and eliminate Sybil nodes [6]. Nonetheless, a centralized trusted authority is not necessarily feasible in vehicular networks, where vehicle mobility and the dynamic network topology substantially hinder the design assumptions behind most attack detection schemes [26].
In vehicular networks, there is an urgent need to explore attack mitigation strategies as it was done in wired P2P networks in order to minimize the malicious effects of the Sybil attack. For example, one mitigation strategy is to disrupt the activity of the Sybil node. However, this is not directly applicable to vehicular networks, because in the case of a Sybil attack with multiple Sybil identities, the strategy must detect multiple malicious nodes consequently, thus degrading the communication and performance of the vehicular network. Hence, the attenuation of the attack impact on the performance of the network remains a critical defense aspect.

This article addresses the gap of enacting the right security posture in ITS environments susceptible to Sybil attacks, particularly their evolving versions, which strategically target multiple traffic controllers to exacerbate the interference with the decisions of traffic flow management applications overseeing networked intersections. These attacks will gain control over a significant part of the network to influence unfavorably the TMC in various network operations. An attacker with multiple fake identities can maliciously participate in a data aggregation process, take advantage of resource allocation mechanisms, disrupt vote-based mechanisms, and interfere with traffic flow management and navigation applications. A defense system assuming a centralized trusted authority is less likely to be feasible in the ITS.

3 THREAT MODEL

ITS reliability is highly dependent on the quality of data collected across the system. This section describes a yet-unexplored threat model that targets data integrity in AMATSC.

3.1 Coordinated Data Corruption: The Case for Sybil

In normal settings, the vehicles send a message to indicate their position and arrival time when approaching a traffic controller. Hence, the latter is fully aware of the number of vehicles in each lane. To generate signal-timing decisions, the queue-based control algorithm will take into consideration the perceived number of vehicles as the queue length, while the delay-based algorithm will extract the vehicles’ delay at the intersection from their broadcasted arrival times. In MARL-based AMATSC, this information will be used in the stochastic game to estimate the transition probabilities between the different states. Hence, corrupting this information will push the controllers off the optimal policy distribution.

A Sybil attack on traffic controllers consists in creating or forging fake vehicle identities and using them to broadcast traffic-related information that may compromise the decisions of traffic flow management applications. This attack is considered indirect since it does not require one to physically access the traffic controller, but to tamper with data transmitted by the network of CAVs, which makes it highly feasible in reality. This article explores an evolved version of a Sybil attack, which we call a coordinated Sybil attack, that will mainly target highly interconnected systems. In this scenario, the attacker will make use of fake vehicle identities to simultaneously target multiple traffic controllers by distributively corrupting their data inputs with the intent of producing a larger attack impact. This can substantially degrade the performance of ITS applications that rely on multiple networked data sources to generate decisions and take actions.

For MARL-based multi-agent systems, this threat can be seen as a direct distortion of the environment on which the agents rely to compute their rewards and derive their policies. In the case of AMATSC, the state of the environment is defined as a vector in terms of the queue lengths associated with each signaling phase \(^9\). The agent’s action consists in producing a variable phasing sequence where the controller will either extend the current phase or switch to a new phase according to traffic variations. Finally, the reward of the agents is determined as the reduction in total cumulative delay \(^9\).
3.2 Threat Impact

By optimally dispersing the attack load, the attacker is not only motivated by the greater scale and consequence of the attack but also seeking to hide it from anomaly-based intrusion detection systems that may raise security alarms if the attack is concentrated onto a single controller. Also, the number of fake identities generated by the attack onto a single traffic lane should adhere to the traffic flow capacity of the lane to avoid raising an intrusion flag. The attack assumes the ability of the malicious vehicle to compromise its OBU and transmit malicious messages. This can be performed physically, wirelessly, or via malware [20].

The impact of coordinated data corruption attacks increases substantially when simultaneously targeting multiple networked intersections controlled by an AMATSC algorithm, as proven experimentally later in this article. For instance, Sybil vehicles within the network are simply regarded as fake messages, but the RSU deploying AMATSC functions actually receives these messages. Thus, the traffic light state may change to discharge traffic that is not really present. Hence, the lanes carrying the actual traffic can become extremely congested because the presence of Sybil vehicles altered the data received by the MARL agents and used by the algorithm in the optimization of timing plans. This attack coordination is required to incur a substantial impact on the different MARL agents compared to a single-agent TSC. As explained above, the adaptive TSC environment requires more sophistication from an attack perspective since the MARL agents correlate their collected information to derive their optimal traffic control policies.

3.3 Attack Assumptions

In the coordinated Sybil attack, the attacker’s goal is to maximize the impact on decision making while minimizing the probability of detection. Hence, the attacker will deploy the Sybil nodes under strategically placed RSUs, the ones that the attacker thinks will influence the decision of the TMC the most according to the perceived delay. The attack can be driven by political or financial incentives, or may be carried out to cause damage to city functions and individuals (e.g., terrorism). We assume that the attacker has sufficient resources and incentives to monitor the traffic on the target networked intersections for long periods of time. The attacker also has full knowledge of the intersection map. Hence, before attacking an intersection, the attacker is assumed to have performed sufficient reconnaissance and thus have studied beforehand the appropriate timing to launch the attack in order to create the most impact, which could be specific to the target junction (e.g., targeting rush hour). We assume that the attack is coordinated by the same adversary via a compromised vehicle botnet, where the malware controls the transmission of Basic Safety Messages (BSMs) at each intersection by following the commands of the main adversary vehicle (these messages are used by the TSC to estimate the queue length). Also, the vehicle bots make use of a specialized software to generate forged pseudonyms and use them to broadcast the malicious BSMs. Our threat model leverages data transmission as an attack vector without the need to directly target the traffic controller.

We assume that the attacker is only interested in manipulating the number of vehicles in a single direction, and thus deploying fake identities on opposite directions is not useful. The attacker can define the critical signal phases to target for increased impact. Although trying out all attack scenarios guarantees the optimal attack strategy, it is unrealistic for an attacker to enumerate them all and find out the best strategy in real time based on the observed attack impact, which needs to be effectively estimated. Thus, a simple greedy attack policy is usually proposed to find an effective attack strategy that yields a sufficient impact according to the attacker. Nevertheless, our proposed game model will enable the attacker to apply an optimal attack policy by solving an optimization problem that produces the best-case attack scenario.
4 ATTACK MITIGATION: A MINIMAX GAME

This article proposes a coordinated Sybil attack mitigation scheme as a resilience-by-design approach to be integrated into the decision-making phase of AMATSC systems, providing real-time, dynamic protection in adversarial scenarios.

4.1 Game Overview

Game Theory has been widely applied to solve a variety of security problems in computer and communication networks. In this article, we design a minimax game theoretical model to describe the interactions between the AMATSC algorithm and the attacker. By solving the game, the algorithm determines the optimal defense strategy to deploy in order to minimize the impact of the attack in the worst-case scenario.

The data corruption attacker can implement a mixed strategy of attack actions by targeting the traffic intersections with different magnitudes based on the estimated potential impact. This also allows the attacker to mask the effects of the attack while prolonging its duration. The payoff of the attack is quantified in terms of the impact on traffic flow at the target intersections. On the other hand, the AMATSC algorithm is not aware of the intersections being targeted by the attack; hence, it must estimate the impact based on the status of the traffic network and consider the information received by each controller accordingly, even though this might entail a cost associated to disregarding some legitimate vehicle messages. The resilience layer proposed in this article is agnostic to the attack strategy and aims to prepare the system to function in the worst adversarial setting without prior knowledge of attacked traffic controllers.

The proposed game is a zero-sum game in which one player’s payoff is the negation of the other player’s payoff. The game is simultaneous, since the defense strategy is implemented regardless of the attack status and is considered as an additional security layer, which is independent from the attack detection functions in place. This recursively played game can be considered as a single-state stochastic game, which will be solved by stationary strategies that do not depend on history and time slots.

4.2 Attack and Defense Strategies

In the cybersecurity battle between the attacker and traffic control algorithm, a set of attack actions is represented by $\mathcal{A} = \{a_1, \ldots, a_j, \ldots, a_A\}$, where $A$ is the size of the attacker’s action profile. The pure strategy $a_j$ consists in targeting lane $j$ each time. The mixed strategy in this case consists in defining a probability distribution vector denoted by $\alpha = (\alpha_1, \ldots, \alpha_A)$, such that $\alpha_j \geq 0 \forall a_j \in \mathcal{A}$ and $\sum_{a_j \in \mathcal{A}} \alpha_j = 1$, to attack the network of intersections with different rates of Sybil vehicles. It is intuitive to assume that the size of the action profile is equal to the total number of traffic lanes at all target intersections.

The TMC controlling the AMATSC algorithm implements the mitigation approach through a set of actions represented in the set $\mathcal{D} = \{d_1, \ldots, d_i, \ldots, d_D\}$, where $D$ is the size of the defender’s action profile. As in the case of attack actions, the defense actions will also be applied at the lane granularity level, assuming that each lane is governed by a distinct traffic controller. Hence, it is intuitive to assume that the size of the attack and defense action profiles is the same.

The AMATSC algorithm usually takes the calculated average speed of vehicles present at the traffic light as input and generates the signal timings accordingly. A pure strategy $d_i$ consists in considering all the vehicles in lane $i$ when computing the input average speed. Adopting a mixed strategy of defense that mitigates the attack impact consists in modifying the input vector to the AMATSC algorithm over all lanes according to a probability distribution vector produced by the solution of the game over the actions in $\mathcal{D}$. The vector is denoted by $\beta = (\beta_1, \ldots, \beta_D)$, such that
\( \beta_i \geq 0 \ \forall d_i \in \mathcal{D} \) and \( \sum_{d_i \in \mathcal{D}} \beta_i = 1 \). Our mitigation solution aims to find the optimal vector \( \beta \) and integrate it into the design of the traffic control logic to reduce the coordinated Sybil attack impact. To account for the presence of a data corruption attack, the algorithm will make use of our game solution to regulate the collected data from the environment in a way that reduces the attack impact based on the predicted effect on traffic congestion. Hence, no elimination of any vehicles is done. The proposed solution is deployed on top of the MARL-based TSC algorithm as a resilience-by-design approach that is supposed to operate without the need to detect the Sybil vehicles, which is one of the highlights of our mitigation solution (compared to previous approaches where the Sybil vehicles need to be identified and eliminated).

### 4.3 Payoff Matrix

The payoff of the attacker can be determined based on the type of the data corruption attack and the caused impact. In the case of coordinated Sybil attacks, the payoff of the attacker is equal to the difference between the maximal flow on the traffic lane, denoted by \( \theta_i \), and the actual traffic flow on that lane, denoted by \( f_i \). These parameters are particularly chosen as they allow to effectively estimate the attack impact. The utility matrix created in our game model is a square matrix of size \( D \), which is equal to the total number of segments on the networked intersections. Each row corresponds to a defense action that may be adopted by the AMATSC algorithm, which in this case represents the lane selected by the traffic controller and whose data is fed as input to the scheduling algorithm to generate the signal timing plan. On the other hand, each column corresponds to an attack action, which mainly represents the target traffic lane.

The attacker must maximize the attack impact on the decisions of the AMATSC algorithm by attempting to corrupt the collection of input traffic data from the lanes as unfavorably as possible. Thus, the utility matrix \( U \) of the attacker, which is used to compute the attacker’s payoff over the set of possible strategies, can be defined in terms of the attack impact by

\[
U_{ij} = \begin{cases} 
\theta_i - f_i, & i = j \\
0, & i \neq j. 
\end{cases} \tag{1}
\]

The impact is equal to 0 when the AMATSC algorithm does not consider the target lane in its decision making. On the other hand, when \( i = j \), the algorithm takes into account only the traffic data of lane \( i \) to generate signal timing decisions (i.e., pure strategy) while the attacker targets the same lane using the Sybil vehicles. Hence, the attack impact is maximal, because the input data is completely corrupted and was perceived by the algorithm as fully accurate.

However, the AMATSC algorithm does not intend to deploy pure strategies, since its main function consists in observing the states on all intersections involved. The goal is then to apply the mitigation procedure on the input data vector itself before feeding it to the algorithm. Hence, the mixed strategy is reflected by the assignment of distinct degrees of confidence in the perceived traffic parameters on all lanes according to the probability distribution vector \( \beta \) generated by the game. For example, a value \( \beta_1 = 0.6 \) will dictate that the algorithm only considers 60% of the vehicles present on lane 1 when computing the associated input data instead of 100% of the vehicles, in an attempt to anticipate the load of Sybil nodes on that lane and reduce its effect. The definition of this utility matrix leads to an AMATSC vs. attacker zero-sum game, where the payoff of the algorithm is equal to the negation of the payoff of the attacker. In other words, the algorithm would lose what the attacker would gain, and vice versa.

### 4.4 Game Model

Based on the above definitions of attack and defense action spaces as well as payoff matrices, we propose a two-player zero-sum minimax game, in which the objective of the attacker is to
distribute the Sybil attack load over the set of traffic segments to maximize the attack impact, and the objective of the traffic control algorithm is to determine the optimal input data vector. The attacker problem is defined as follows:

\[
\text{Maximize } \min_{d_i \in D} \sum_{a_j \in A} U_{ij} \alpha_j
\]

Subject to:

\[
\sum_{a_j \in A} \alpha_j = 1
\]

\[
\alpha_j \geq 0 \forall a_j \in A.
\]

A maxmin strategy is one that maximizes the player’s worst-case payoff. Here, the attacker tries to maximize the minimum impact of the Sybil attack by computing a probability distribution vector \( \alpha \), according to which the attack will be distributed over the set of traffic controllers. The optimization problem is not linear but is equivalent to the following linear program:

\[
\text{Maximize } \rho
\]

Subject to:

\[
\rho \leq \sum_{a_j \in A} U_{ij} \alpha_j \forall a_j \in A
\]

\[
\sum_{a_j \in A} \alpha_j = 1
\]

\[
\alpha_j \geq 0 \forall a_j \in A,
\]

where \( \rho \) is a variable defined for problem linearity. We try to maximize the value of \( \rho \) while adhering to Constraint 6. The problem can now be solved using the simplex method in polynomial time.

When considering the problem from the perspective of the traffic control algorithm, the optimal defense strategy, represented by the probability distribution vector \( \beta \), is derived by solving the following optimization problem. This is the minimax strategy that represents the mitigation approach:

\[
\text{Minimize } \max_{d_i \in D} \sum_{a_j \in A} U_{ij} \beta_i
\]

Subject to:

\[
\sum_{d_i \in D} \beta_i = 1
\]

\[
\beta_i \geq 0 \forall d_i \in D.
\]

This conservative strategy introduces potential resilience against Sybil attacks. This is equivalent to minimizing the largest attack impact that may occur in the worst-case scenario. That is, the AMATSC’s objective is to minimize the maximum attack impact (i.e., minimize the attacker’s payoff).

Based on the nature of traffic parameters usually exploited by current and emerging AMATSC algorithms, the vulnerability of these algorithms against data corruption attacks, particularly Sybil attacks, cannot be completely eliminated. Hence, we argue that an effective approach is to prepare the algorithm to deal with such attacks if ever materialized. Following the same mathematical transformations explained earlier, the nonlinear optimization problem becomes
Minimize $\phi$  
Subject to: 

$$\sum_{d_i \in D} U_{ij} \beta_i \leq \phi \quad \forall d_i \in D$$

(13)

$$\sum_{d_i \in D} \beta_i = 1$$

(14)

$$\beta_i \geq 0 \quad \forall d_i \in D,$$

(15)

where $\phi$ is defined to make the problem linear and should satisfy Constraint 13. The two problems defined in Equations (5) and (12) are dual. The duality theorem explained in [18] states that the maximum payoff that the TMC can achieve is equal to the minimum payoff that the attacker will receive. This is usually known as the “value of the game” and is achieved at the equilibrium point.

5 IMPLEMENTATION DETAILS

The lack of large-scale deployment of CAVs and technology limitations make theoretical analysis and simulation the main choices in the validation of our study. The realism of the simulation is thus a paramount aspect. To reproduce the road traffic network, we adopted the open-source microscopic traffic simulation package Simulation of Urban Mobility (SUMO) [15]. SUMO has a Python Traffic Control Interface (TraCI) that interfaces it with an external application via a TCP socket connection. It permits SUMO to connect to other systems, such as the monitoring and control system. In fact, the TraCI interface allows the integration of Flow [7], a computational framework for deep RL and traffic control experiments.

5.1 AMATSC Simulation Setup

It has been proven that an RL agent is capable of learning policies exceeding the performance of state-of-the-art traffic signal control programs [19]. Flow enables the use of a single agent to control an intersection with RL or a multi-agent algorithm to control a network of intersections (e.g., one controller agent acting on three intersections at the same time based on data collected from all three intersections). In this work, the implementation of MARL is contemplated as it is in this case that the benefits of learning should be most apparent and useful in the context of traffic signal control. RL-based AMATSC algorithms use different parameters as input to the RL algorithm. Among the data gathering techniques that assess the different parameters, we leverage the capabilities provided by the CAV technology within the traffic network and model them in Flow. Features are then extracted from the SUMO environment and provided as input to the control algorithm implemented in Flow.

Flow integrates SUMO with a standard deep RL library rllab, thereby permitting the training of large-scale RL experiments for traffic control tasks. Also, Flow can be used to simulate CAV-based traffic control to enforce state changes in the traffic light program at the intersection. The changes in the traffic signal at intersections are dictated by the RL control component implemented in Flow, thus providing sophisticated, adaptive RL-driven traffic light programs. We used the configuration of the Proximal Policy Optimization (PPO) control algorithm, which is a policy-based RL method with significantly less computational complexity than other policy gradient methods [21]. We train the PPO RL agent under normal traffic conditions and obtain the resulting policy.

5.2 Evaluation Metrics

The mean trip waiting time is used as a performance metric to measure the impact of traffic control performed at each intersection compared to a baseline where static traffic programs are implemented. The waiting time represents the time in seconds during which the vehicle speed is below...
When RL agents are deployed, the waiting time of vehicles going through the network of controlled junctions decreases. In a stochastic traffic environment, in order to establish useful ranges for the waiting time metric, many simulation runs are performed and the mean trip waiting times are averaged. We implement several scenarios to assess the trip waiting time under normal traffic conditions, under coordinated Sybil attacks, and when a mitigation solution is deployed.

5.3 Baseline Scenario

In the baseline scenario, traffic is flowing under normal traffic conditions. Moreover, the control logic implemented at each intersection is one of the types available in SUMO, which is either static or actuated (gap based or delay based). Vehicles will send a message to indicate their position and arrival time when they approach a traffic light. We identify three adjacent intersections in the transportation network and collect the mean trip waiting time of the vehicles going through the identified intersections under this control logic.

This scenario serves as the baseline for the evaluation of this metric. A MARL-based AMATSC managing the three intersections will aim at improving this metric. On the other hand, a coordinated Sybil attack on the network of intersections will try to degrade it. A repository reproducing the scenarios and results can be found at https://github.com/LiTrans/UrbanSybil/.

5.4 MARL-based Control Scenario

In this scenario, we run the experiment under normal traffic conditions with a trainable RL agent using the PPO algorithm to control the three intersections. The PPO algorithm requires the definition of state, action, and reward to train the traffic lights. The state corresponds to the agent’s observation of the current environment, which includes the number of vehicles in each intersection observed as the closest to the traffic light. Particularly, the state space that is partially observed consists of the velocities, distances to the intersections, edge number from each direction, edge information, and traffic light states. The model uses the observation to compute the average velocity and flow density on each edge.

The model also keeps a multi-dimensional array to keep track of how much time has passed since the last change to yellow for each traffic light, as well as to keep track of the flow direction and whether or not each traffic light is currently yellow. Results from SUMO are used by Flow for the generation of observations. The action space specifies whether a traffic light is supposed to switch or not. The actions are sent to the traffic lights in the controlled network of intersections. The reward represents the negative value of per-vehicle delay minus a penalty for switching traffic lights. It is the reward associated with the previous state/action pair.

The multi-agent environment provided by Flow enables the specification of the number of lights that the agent can observe (we set this number to three traffic lights in our simulation). The state space in this context corresponds to the velocities, distances to intersections, edge number from each direction, and traffic light states of all three intersections. Hence, it represents the multi-agent shared model version of the network. The RL-based adaptive traffic signal controller issues an action for each traffic light agent. An agent receives a reward normalized by the number of lights.

An experiment run in this scenario returns the trained RL model as a result. The final policy mapping is returned by the simulation. We then save the trained model to replay it by simply loading it. Since the algorithm requires a vectorized environment to run, we provide a reward of value 0 and an observation vector. The model is then able to predict the actions to take at each intersection of the network based on the observation provided. Thus, the model maps the states to actions to be performed. Actions from the policy are provided to the SUMO simulator. There is a minimum switch time implemented in the algorithm for each traffic light so that earlier RL commands are ignored.
5.5 Coordinated Sybil Attack Scenario

The transportation network allows vehicles to frequently join and leave. This type of network is susceptible to Sybil attacks, in which an attacker gains influence by joining a network under multiple colluding aliases. The traffic control algorithm exploits the data sent by the CAV in the range of an RSU to generate optimal signal plans. At all times, the RSU is fully aware of the number of vehicles by counting the number of messages received from both the Sybil and legitimate vehicles. The controller will consider any of the following metrics in the scheduling algorithm: number of vehicles, arrival time of each vehicle in each lane, vehicle speed, and vehicle delay, thus deriving other macroscopic metrics at the intersection. Consequently, every single vehicle within the RSU’s communication range can potentially affect signal timing decisions.

We simulate the coordinated Sybil attack in SUMO by injecting virtual vehicles. We vary the number of injected vehicles and the time and the duration of the injection. To measure the impact of the attack, trip waiting times of Sybil vehicles are not considered in the computation of the mean trip waiting time metric because they simply do not exist. Thus, we consider only the trip waiting times of real vehicles and compare them to the baseline scenario, where traffic is flowing under normal traffic conditions, e.g., no attack on AMATSC. In our coordinated Sybil attack implementation, the attacker deploys Sybil vehicles per each RSU. Thus, the network of three intersections controlled by the RL algorithm is targeted with different Sybil arrival rates at every intersection. To reflect a generic attack scenario where the attacker is not necessarily intelligent, we implement an attack strategy where the attacker targets the critical phase that causes the largest delay, instead of implementing the best-case attack scenario generated by our game. Hence, each traffic signal in the network is identified as a potential attack target. The measured attack impact was substantial even when the optimal attack policy was not adopted. Nevertheless, our mitigation approach is designed to deal with the worst-case attack scenario.

5.6 Threat Mitigation Scenario

Here, we implement the minimax game as a mitigation layer on top of the control layer. Figure 3 illustrates the defense strategy as a layer of protection against coordinated data corruption attacks on the AMATSC application regardless of intrusion detection performance. To reduce the attack impact, this layer will adjust the inputs provided by SUMO to the AMATSC algorithm implemented in Flow. First, we need to compute the maximum flow on the 12 traffic segments of the intersections controlled by the RL agent (three junctions, each having four segments).

Figure 4 shows the variation of traffic flow on an urban road network. Macroscopic stream models represent how the behavior of one parameter of traffic changes with respect to another. Precisely, the relation between the flow and density of an edge is shown in Figure 5. Also, the assumed linear equation between speed and density is given by

\[ v = v_f - \left( \frac{v_f}{k_j} \right) \times k, \]  

(16)
where $v$ is the mean speed at density $k$, $v_f$ is the free speed, and $k_j$ is the jam density. The relation between flow and density can be derived using $q = k \times v$, thus getting the following parabolic equation:

$$q = v_f \times k - \left(\frac{v_f}{k_j}\right) \times k^2. \quad (17)$$

Finally, we derive the relation between speed and flow:

$$q = k_j \times \left(\frac{v - v^2}{v_f}\right). \quad (18)$$

Once the relationship between the fundamental variables (density, flow, speed) of traffic flow is established, the boundary conditions can be derived. The one of interest is the maximum flow. From Equation (18), we find the critical density at the maximum flow using the following derivative:

$$\frac{dq}{dk} = v_f \times \left[1 - 2 \times \left(\frac{k_c}{k_j}\right)\right] = 0 \quad (19)$$

$$k_c = \left(\frac{k_j}{2}\right). \quad (20)$$

Therefore, the density corresponding to maximum flow can be approximated by half the jam density. Once we get $k_c$, we can derive the maximum flow, denoted by $q_{max}$:

$$q_{max} = \left(\frac{v_f \times k_j}{4}\right). \quad (21)$$

Thus, the maximum flow is approximated by one-fourth the product of free flow and jam density. In the second part of the scenario, we extract from the simulation the current flow observed on the segment of interest and compare it to the maximum flow:

$$\Delta = q_{max}(t) - q_{actual}(t). \quad (22)$$

From the perspective of the attacker, the aim is to inject Sybil vehicles on the edges that best suit the attack’s goal according to the current observations of density and flow. Particularly, the
attacker will consider the edges where density is low to medium and the maximum injection rate will be dictated by $\Delta$. Knowing that the RL agent keeps track of the average velocity of the vehicles observed, the attack will aim to decrease the average speed, thus inducing the model to propose suboptimal actions. The minimax game mitigates the attack by limiting the influence the attack achieves through the Sybil nodes.

To this end, this scenario consists of the implementation of the defense optimization problem in Equation (9). The output of the proposed minimax game is the vector $\beta$ corresponding to the weights of information collected on each edge (e.g., its reliability). Such high-level weights could be interpreted in a variety of ways depending on the traffic control module under investigation. This is one of the advantages of our proposed game model, which offers a relative level of flexibility in how the mixed strategy of mitigation actions would be actually implemented. In our simulation, each element of the vector corresponds to the percentage of vehicles to be considered on each edge at each iteration $t$ by the RL agent for the computation of the input average speed. These values represent the modified inputs fed to the control layer as the new state observed by the MARL agents, which is the most fundamental component of our resilience-by-design scheme.

6 EXPERIMENTAL RESULTS

To demonstrate that the discovered security flaws have high practical implications, this section assesses the impact of the coordinated Sybil attack on a realistic transport network and provides the results of the mitigation strategy, which can be deployed to protect existing and emerging ATSC systems.

6.1 Impact of Coordinated Sybil Attacks

We perform the attack on the real urban network of the city of Montréal using real-world traffic data and signal timings.

6.1.1 Dataset Description. Information on traffic demand in Montréal was obtained in the form of an Origin-Destination matrix (O-D matrix) from the Survey of the Montréal Metropolitan Area carried out in 2013 by the provincial government. The zone corresponds to the city downtown and occupies an approximate area of 4 km$^2$. We also used the information on the traffic signal plans of the modeled network for the period of 8 AM to 9 AM, provided by the Transport Division of the City of Montréal. The dataset does not include trips of pedestrians, cyclists, public transport (buses), or commercial vehicles (trucks). The traffic conditions of the Montréal road network were experimentally reproduced under normal conditions in SUMO as per the baseline scenario. The real road network of Montréal was also used in the coordinated Sybil attack scenario.

The traffic scenario used in our simulations fulfills a wide range of requirements needed to reproduce realistic mobility patterns. In fact, the scenario was able to support different kinds of traffic demand, such as congested and free-flow patterns. It also included different road categories (e.g., residential, arterial, and highway) and supported different scenario dimensions. The scenario contained information on both traffic demand and traffic signal plans from a real network for the period of 8 AM to 9 AM, which is considered the morning rush hour in any urban network. This is the most critical hour of the network operations and any attack at this time can result in the most impact. In the simulation of the city traffic, SUMO, the microtraffic simulator, uses the actual origin-destination matrix based on real data in combination with the routing algorithms and realistic traffic signal plans to reproduce the trips. The traffic simulation itself is first calibrated and validated with real data. Moreover, the scenario avoided gridlocks and unrealistic mobility patterns. In fact, from the short report provided by SUMO at the end of the simulation, we notice that all the issues (e.g., teleports and emergency stops) that may be experienced by a vehicle
during the simulation are lower than 0.2%, indicating that the scenario is running smoothly without bottlenecks and gridlocks.

6.1.2 Results and Analysis. The realistic evaluation of the impact of the coordinated Sybil attack in terms of mean trip time loss demonstrates the potential physical impact of real cyber-physical attacks, which exploit the perception layer to target the application layer. We validate that there is no need to rely on assumptions of the effect of attacks against the traffic control components and that our mitigation has solid merit in improving the resilience of these components. We provide results for both the baseline and Sybil attack scenarios on one junction and three networked junctions of downtown Montréal.

We identified the 50 most critical traffic lights based on the average mean time loss in several simulation runs. Figure 6 shows the mean trip waiting time of the most critical junction. This junction is controlled by a gap-based actuated traffic control. This control scheme works by prolonging traffic phases whenever a continuous stream of traffic is detected. It switches to the next phase after detecting a sufficient time gap between successive vehicles. This allows for better distribution of green time among phases and also affects cycle duration in response to dynamic traffic conditions. We considered the maximum time gap to be of 3 seconds between successive vehicles that will cause the current phase to be prolonged. The minimum duration and max duration of green time are 5 and 45 seconds, respectively.

Figure 7 shows the impact of Sybil attack on the same junction as the baseline scenario. Sybil vehicles were injected around the junction long enough to be detected by the RSU, which then receives the wrong information about the state of traffic flow. The Sybil attack increased the mean trip time loss by approximately 23 seconds compared to the baseline.

Since AMATSC is not yet deployed in the transportation network of the city of Montréal, Figure 8 shows the average mean trip waiting time of vehicles on three neighboring but isolated intersections under the baseline scenario. In the next section, we demonstrate that, if the junctions were interconnected and AMATSC was implemented, the performance in terms of trip time loss is improved. Figure 9 shows the impact of the Sybil attack on the same three junctions. The junctions are also controlled by a gap-based actuated traffic control. We notice that the trip time loss under attack increased by 34 seconds, that is, approximately by up to 50% more than the Sybil attack targeting a single junction.

In [27], they presented a study on the impact of time spoofing attacks on different traffic signal control algorithms in single and multiple intersections under both homogeneous and
heterogeneous arrivals. They showed that the delay-based scheme is more vulnerable to time spoofing attacks compared to the sum-of-delay-based scheme. In addition, the hybrid scheme that combines delay-based and queue-based schemes performs similarly to the queue-based scheme when under attack. From their conclusions about the time spoofing attack, we can infer the same about our coordinated Sybil attack. We delivered evidence of the damage that can be caused in terms of increasing the time loss under a gap-based control algorithm. It will be further demonstrated that even more substantial damage can be caused under other scheduling algorithms, such as AMATSC.

6.2 Attack Mitigation Performance

The mitigation scenario described earlier is simulated on a grid network topology. We use the pre-built configurable traffic light grid environment implemented in Flow to conduct the simulations. We customized the environment/network parameters as per Table 1. Using the $10 \times 10$ grid network topology, we simulate the baseline scenario under normal traffic conditions, where the traffic light logic exerts control over individual traffic lights using SUMO actuation. In fact, the default SUMO actuated traffic lights are fine-tuned on many iterations with varying parameters of phase duration.
and state. Figure 10 shows the mean trip waiting time around three junctions of the grid network for different scenarios. The dark blue curve corresponds to actuated control and represents the baseline scenario used for the comparison with the other scenarios. The mean trip waiting time is 154.3 seconds.

The red curve in Figure 10 shows the results for the same environment but with three traffic lights controlled by an RL agent. The other traffic lights remain controlled by the default SUMO actuated type of traffic control. This is where we switch from the non-RL to the MARL experiment in Flow to apply RL-specified traffic light actions via TraCI. Precisely, to simulate AMATSC on a network of intersections, we implement the multi-agent experiment where agents use the same policy.

We set the state to be partially observable. The reinforcement learning algorithm needs observations but does not need to observe all the traffic lights that are on the network topology under study. Of all the traffic lights on the 10 × 10 grid network topology, only three of them are controlled by an RL agent for the purpose of adaptive traffic signal control. Thus, we limit the agent’s observation of the current environment as being of only those three specific intersections. The agent does not need full observation of the rest of the traffic lights. This comes from the fact that congestion is a spatio-temporal phenomenon. Events occurring at traffic lights that are very far away from an intersection are not indicative of the congestion status at the specific intersection. In contrast, data from relevant intersections are more of a valid indicator of traffic state at an intersection. There is a rule of thumb in transportation that considers that there is roughly an area
of interest of 2 km surrounding a vehicle or an intersection to describe a traffic situation. Thus, we assume that a traffic situation happening beyond 2 km of a target segment will not have an impact on the traffic flow on the segment. We want the environment to be partially observable so as to better capture the current local view at the intersection.

For each one of the three traffic lights of interest, many values are collected since they will directly impact the model. Inputs from all the lanes are observed and taken into account such as the number of vehicles per lane, the velocity of every vehicle on each lane, distances to the intersections, edge number from each direction, edge information, and traffic light states. This subset of information is then provided to the controller. Each agent is considered as a single intersection controlling its traffic lights. The observation space is defined as normalized velocities of nearby vehicles, for every intersection. We set the action space to be discrete (e.g., the action space specifies whether a traffic light is supposed to switch or not) and to directly match the number of traffic intersections to be controlled. Because of the shared policy, instead of computing the actions, state, and reward for a single agent, as a reward, the RL-based controller will penalize the large delay and boolean actions that indicate a switch (with the negative sign) for all the controlled agents in the network. The same policy is used by each agent, and actions from the policy are provided to the SUMO simulator.

We notice from Figure 10 that MARL-driven control is able to decrease the mean trip waiting time by approximately 52.4 seconds compared to the baseline scenario on three actuated traffic lights under normal conditions. We then run the coordinated Sybil attack scenario on the grid network with three traffic lights controlled by an RL agent and present the results in Figure 10. The green curve shows the attack’s impact on adaptive traffic control. The increase of approximately 97.7 seconds compared to the RL-based control scenario motivates the need for mitigation, which proves to be required to limit the impact of this sophisticated attack on AMATSC.

In Figure 10, the purple curve presents the results of the optimal mitigation strategy when the network of intersections is the target of a coordinated Sybil attack. We are able to improve time loss by approximately 48.9%. Our design proves to mitigate the attack by limiting the influence the attacker gains through Sybil nodes. Moreover, we realize that the optimal strategy performs better than the baseline, which validates the fact that we can’t just ignore the link that has an attack for a certain time or minimize its effect by switching to fixed time plan control or actuated control instead of adaptive controller without applying our mitigation strategy. On the other hand, the performance of RL-based control when the mitigation approach is applied (purple curve) would still be degraded compared to its performance under normal settings (red curve). As expected, the mitigation solution is designed to attenuate the attack’s impact, not to eliminate it completely.

Figure 10 compares the performance of the optimal mitigation strategy with respect to the fair strategy wherein the mitigation does not consider the probability distribution vector $\beta$ generated by the minimax game solution, and which corresponds to the percentage of vehicles to be considered in the algorithm’s input on each edge as part of the mitigation process. Instead, the fair strategy modifies the weighted speed values on each edge by taking the same number of vehicles present on each edge regardless of which edge might be more impacted by the coordinated Sybil attack. This strategy does not account for the potential presence of coordinated Sybil vehicles within the network, which attempt to achieve a high-impact attack by optimizing their presence on the networked traffic edges. Hence, this strategy is not supposed to provide optimal mitigation, simply because it does not ponder the payoff matrix that we created in Equation (1) and is not prepared to deal with the worst-case attack scenario.

In our simulation, the fair strategy considered half of the number of vehicles present on each edge of the intersections controlled by the RL agent for the computation of the average speed on that edge at each iteration. The light blue curve shows that the fair strategy improves time loss
incurred under a coordinated Sybil attack by approximately 26.5%. As expected, the fair strategy does not perform as well as the optimal strategy, and thus is not appropriate to implement as part of a resilience-by-design defense approach.

Figure 11 presents the results when the mitigation approach is activated without the Sybil attack compared to the other scenarios. Compared to the RL control under no attack, the performance was slightly degraded by approximately 25% but is still better than the actuated control performance, which justifies the activation of our mitigation approach even in the absence of an attack. Based on our obtained results, deploying resilience-by-design incurs some cost, which makes our approach realistic. Figure 11 mainly aims to evaluate this cost on the performance of traffic controllers; the metric used is the mean vehicle trip wait time. One of the highlights of our proposed scheme is that it does not rely on detecting the attack in order to mitigate its impact. Instead, it operates based on impact prediction and attempts to reduce this impact while assuming the potential presence of an attack. Therefore, the proposed resilient MARL-based control algorithm does not detect the presence of an attack but can operate in a more robust fashion since resilience is always activated.

In our early experimentation, we had studied the impact on the performance of the mitigation when the number of Sybil attackers increases. In fact, injecting a small number of Sybil vehicles did
not result in a decrease in mean trip wait time. Thus, it did not result in a successful attack. Even when we slightly increased the number of Sybil attackers, this had no impact on the traffic. We tested this for different groups of traffic light signals, and for all the different combinations tested, our mitigation performed as per the “Mitigation activated without attack” scenario of Figure 11.

This situation is due to the fact that from the attacker’s perspective, it was not possible with only a few vehicles to impact the traffic signal control on a road segment where there was no traffic congestion. So we needed the attacker to observe the density and the flow values on different road segments in order to identify the ones experiencing the most critical traffic conditions. We had to proceed this way not only for the attacks to be successful but also to actually test our proposed mitigation. Also, in any case, in transportation, adaptive control is not implemented on every traffic light. It is implemented only on a critical network of intersections. In the same manner, mitigation does not have to be implemented everywhere because attacks are less likely on those intersections with light traffic. Thus, we made sure to identify the most critical traffic lights so that the attacks would have an impact and that the mitigation can be evaluated. It was always on congested road segments; otherwise the attacks cannot work, nor is the mitigation necessary because there are no attacks there.

We compare the performance of our model to the mitigation strategy proposed in [12]. We will refer to this mitigation strategy as the baseline mitigation strategy. This mitigation strategy consists of a configuration where the intersection enters a fault state and requires manual intervention to reset. If the traffic light is under attack or an unsafe configuration (e.g., conflicting green lights) is detected, the mitigation strategy overrides the controller and forces the lights into a known-safe configuration (e.g., blinking reds). In other words, this mitigation strategy removes the adaptive control that might be implemented at the intersection and resorts to the traffic lights acting as stop signs. To study the impact of this mitigation strategy on the road traffic network of our study, we simulated three different scenarios, and then in a final scenario, Scenario 4, we compared the results of this mitigation with our proposed mitigation approach.

**Scenario 1:** We ran a simulation to mitigate one traffic light at a time using the baseline mitigation strategy, and we did so for all the traffic lights in the $10 \times 10$ grid network of our study. We computed the mean trip wait time for each simulation based on the wait time recorded for all the completed trips (vehicles having arrived at their destination) during the simulation. We were then able to identify the top nine most critical traffic lights in the network by sorting them based on the measured mean trip wait time metric.

**Scenario 2:** In this scenario, we applied the same baseline mitigation strategy but to groups of random traffic lights. The size of the groups varied between three, six, and nine traffic lights. We ran 20 simulations for each group size, and the traffic lights per group changed from simulation to simulation. Figure 12 shows the distribution of the mean trip wait time values of the 20 simulations with respect to the number of traffic lights per group. The ”0” group represents the mean trip wait time values for the simulations under normal conditions (without mitigation).

The results of this scenario show that as more traffic lights are mitigated with this strategy, the value of the mean trip wait time stays roughly the same, even slightly decreasing in some settings, which represents a positive impact. Once traffic lights are turned off, drivers act as if there are stop signs on all approaches to intersections. In this case, the drivers respect the rules of conduct and do stop at stop signs, giving priority to the other vehicles already at the intersection, before continuing their trajectory. In this scenario, the waiting time at intersections with stop signs could actually be less than at intersections with traffic lights for the duration of the trip. However, the waiting time would increase in cases of pedestrians crossing intersections, but this traffic was not included in the simulations. This situation could have encouraged vehicle movement in the simulations and led to a reduction in small decrease of mean trip wait time.
Scenario 3: In this scenario, we apply the baseline mitigation strategy to the top nine most critical traffic lights that were identified in Scenario 1. However, in the same manner as in the previous scenario, we perform the mitigation in groups of traffic lights. We start by mitigating the first three traffic lights on the list of Scenario 1; afterward, we proceed to mitigating the first six traffic lights on the list; and finally we mitigate the nine most critical traffic lights simultaneously. We ran 20 simulations for each group size. Figure 13 shows the results obtained for this scenario.

The results show that, compared to the normal conditions (0 group that is under no mitigation), the mean trip wait time increased for the cases of three, six, and nine traffic lights attacked. On the other hand, compared to the mitigation of randomly selected traffic lights, the mean trip wait time for the targeted mitigation was higher for all sizes of groups of traffic lights. These results show that the impact of mitigation varies according to the selection strategy. In Scenario 2, traffic lights were chosen randomly, but in this scenario, the traffic lights were chosen based on a performance metric.

Scenario 4: In this scenario, we run the coordinated Sybil attack on the three targeted traffic lights that constitute the network of three intersections controlled by the RL algorithm in our simulation. We first implement the baseline mitigation approach. We then rerun the attack but with our mitigation strategy. Figure 14 shows the performance in terms of mean trip wait time of the vehicles when the network of intersections is controlled by an adaptive traffic control system under a coordinated Sybil attack that is mitigated with different mitigation strategies.

Finally, the penetration rate of CAVs in the first part of our study was 100%. However, in the transition periods of CAVs, of all the vehicles on the road traffic network, only a percentage of them
will be equipped with transceivers enabling them to be connected and autonomous. Considering that such transition periods typically will last a long period of time, it is thus necessary to study and evaluate our proposed mitigation strategy in the presence of mixed traffic (coexistence of regular vehicles and CAVs). A low penetration rate implies that not only fewer vehicles will report their traffic information to the roadside unit but also a low penetration rate may lead to network fragmentation in the vehicular network. It could be the case that CAVs must wait to be in the communication range of each other in order to relay messages, and hence fragmentation will also have an impact on the performance of CAV-based TSC systems. Those systems depend on network connectivity to communicate the microscopic and macroscopic traffic variables. The question that arises in such a case is: what percentage of penetration is enough to obtain the full benefits of our proposed mitigation approach?

To address this question, for every penetration rate, we simulate three scenarios. The first scenario is the one under normal traffic conditions where the traffic signal at the intersections is dictated by the CAV-based RL-driven AMATSC algorithm. We then simulate a scenario where we conduct a coordinated Sybil attack at the studied rate. We did not impose a penetration rate for the attacker. In fact, at any penetration rate, we assume that the attacker can freely inject Sybil vehicles per each RSU regardless of the underlying penetration rate in the network. This will maximize the impact of the attack on the network of intersections. We proceed as follows because we wanted the attacker to sabotage the system in order to study the performance of our proposed mitigation strategy. Otherwise, if we impose that the number of OBUs that can be compromised by the attacker is limited, in order to account for the low penetration rate of the technology, the results we achieved at very low penetration rates for the attack were non-significant. The attacker was not able to impact traffic in a significant manner. Our assumption ensures that the network of three intersections controlled by the RL algorithm is targeted with different Sybil arrival rates at every intersection regardless of the penetration rate. We then perform the threat mitigation scenario where we apply our proposed minimax game as a mitigation layer on top of the control layer. Figure 15 shows the results in terms of mean trip wait time that we obtained at different penetration rates for the different scenarios.

First, we notice that the performance of the CAV-based AMATSC system is impacted by the penetration rate. At lower penetration rates, the mean trip wait time for the RL control scenario is very high. It then decreases as more vehicles participate in the sensing. With regard to this scenario, we consider a 60% penetration rate to be an acceptable value. This is because we expect
the RL control to exceed the performance of state-of-the-art traffic signal control programs. So it is only at a 60% penetration rate that the CAV-based reinforcement learning TSC system performs better than the actuated scenario. We see from Figure 11 that the average mean trip wait time of vehicles in the actuated scenario is 150 seconds. The adaptive TSC system is expected to increase this transportation performance. In Figure 15, at lower penetration rates, the RL control is not performing better than the actuated scenario. It is not able to produce adequate traffic light timing plans because it does not get from the environment the actual traffic demand at the intersections. To study the situation further, we observed the distance between the vehicles in the simulation that are equipped with CAV capabilities. As the penetration rate decreases, the distance between vehicles increases, thus leading to more network fragmentation and lower performance in terms of sensing and reporting to the RSU.

Irrespective of how fast CAVs can broadcast their traffic information to the RSU, the RSU is concerned by the average velocities of the vehicles observed and the flow density on each edge. The average velocity is not the metric that is affecting the overall behavior of the mitigation and the RL control under low penetration rates the most; it is more the inaccurate flow density estimation in very low penetration that is affecting the performance.

In a scenario where CAV penetration is around 20%, the other 80% of vehicles are not signaling their presence on the road segment, thus affecting the flow density observed. However, the average velocities of the 20% CAV-capable vehicles is somewhat of a good representation of the overall velocity on the segment. On the other hand, in a scenario where CAV penetration is around 80%, the 20% that are not reporting their information are not impacting the flow density observed as much. In the first case, the attacker has the upper hand and we notice this by the big difference in mean trip wait time between the Sybil attack scenario and the RL control scenario at a specific penetration rate for the low penetration rate values (e.g., at 20%: 380s and at 40%: 300s). As the penetration rate increases, this difference decreases significantly to 100s observed at a 100% penetration rate. In fact, the decreased connectivity aggravates the vulnerability of AMATSC algorithms to falsified data and erroneous measurement. Finally, we see that our mitigation strategy is able to lower the mean trip wait time in any penetration rate. It decreased it between 54% (for the 20% penetration rate) and 33% (for the 60%, 80%, and 100% penetration rates). Also, our mitigation is showing results that are consistently closer to the normal traffic conditions than to the mean times observed under attack, and this is because, by design, the minimax game is trying to anticipate the load of Sybil nodes and trying to reduce their effect. This analysis has shown that our mitigation requires approximately a 60% penetration rate to obtain the full benefits of CAVs in the context of adaptive TSC. It also showed the robustness of our mitigation strategy under different scenarios.
Finally, RL-based AMATSC algorithms can use different parameters as input to the RL algorithm. Depending on whether the algorithm needs the perceived number of vehicles as the queue length or whether the algorithm needs the vehicles’ delay at the intersection that can be extracted from the broadcasted arrival times to generate signal-timing decisions, we can imagine that our mitigation might be impacted even less by the penetration rate. In a future work, since our method is based on an infrastructure-less approach, it could be interesting to investigate how much of a lower penetration rate can be achieved with a mix of infrastructure-based and infrastructure-less approaches.

7 DISCUSSION

We have proven that the threat posed by sophisticated attacks on traffic control systems is of particular concern. To counter this threat, the first line of defense is to implement detection solutions. However, most of the state-of-the-art Sybil attack detection approaches have serious shortcomings. To be effective, a detection approach requires precise knowledge of the actual system being controlled and the control discipline employed. Traffic control systems are highly vulnerable to cyber-physical attacks, and domain-agnostic security solutions are too generic to be able to comprehend and detect intelligent, sophisticated attacks. In critical infrastructures such as ITSs, the attack can cause physical, disruptive damage. Therefore, a proactive defense solution is required, without necessarily relying on attack detection. This article proposes an effective mitigation strategy that can be integrated into the application layer, providing resilient-by-design AMATSC systems.

In fact, several works discussed the tradeoffs that exist among seemingly different system security properties such as confidentiality, integrity, and availability. Nonetheless, progress toward operational cybersecurity is critical, including the evaluation of operational consequences and tradeoffs of possible protections. Understanding the tradeoffs and the issues that arise when those security properties are all in play is part of a risk assessment strategy. In networked cyber-physical systems, once security goals are identified, risk/benefit assessments can be performed for informed decision making about cyber-physical system security. For example, in the context of the AMATSC system under study, a decision might be to activate the mitigation depending on the traffic mobility during rush hour (high density), during the day (moderate density), and during the night (low density). The right security posture would be dictated by a threat-based security methodology to completely identify system vulnerabilities and quantify the effectiveness of the mitigation against those vulnerabilities in order to evaluate operational consequences.

Moreover, to maintain an optimal performance of the RL-driven traffic control, the proposed mitigation approach is not required to be deployed at all times. It can be adopted at the application layer when the control logic has suspected an attack and must be proactively prepared to face its impact on decision making. The proposed mitigation solution constitutes an invaluable line of defense to integrate within a defense-in-depth strategy in highly vulnerable environments running in adversarial settings. It is the first step toward the design of an adaptive cyber-physical security approach tailored to traffic control systems. Also, one of the highlights of our mitigation solution is that it does not rely on the detection and identification of Sybil nodes to mitigate the attack impact, unlike most of the existing solutions.

On a real-world traffic control system, the mitigation approach will be deployed at the TMC as an add-on feature on top of the traffic control software application as a way to reconstruct the input parameters of the control algorithm and dynamically generate the traffic control actions in real time (the algorithm outputs are based on the prediction of attack impact on networked intersections). This implementation consists in building by-design resilience by embedding the adaptive mitigation algorithm into the control code of the learning module.
8 CONCLUSION AND FUTURE WORK

A new and emerging challenge to the design of AMATSC algorithms is explored. We stress the fact that the implementation of the traffic control logic should be attack aware. We present a new, highly realistic threat model, namely, coordinated Sybil attack, that targets a network of intersections controlled by adaptive control algorithms to sabotage their decision making. We implement the attack and investigate its impact using a real traffic dataset under real-world intersection settings. The obtained results as well as the exposed vulnerabilities of emerging AMATSC systems should be taken seriously when pondering future design choices and implementations.

To respond to anticipated intelligent data corruption attacks against AMATSC, we present a mitigation strategy as a layer of protection in case of detection failure. The devised minimax game model enables the AMATSC algorithm to make optimal decisions under attack. The optimal mitigation strategy showed a substantial improvement of time loss by approximately 48.9%. It can be potentially integrated at the application layer as part of a resilience-by-design approach.

In the future, we will study the impact of our coordinated Sybil attack on different traffic control algorithms with regard to the metrics used. Some AMATSC algorithms may be more vulnerable than others to our attack. Hybrid schemes that combine metrics may perform better when under attack than schemes that use single metrics. Similarly, the effectiveness of the mitigation may vary depending on the deployed control algorithm, which requires further investigation. We are currently working on designing an adaptive traffic control strategy based on impact prediction on various lanes to randomize the deployment of the resilience scheme and reduce its cost on performance.

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