

Vulnerability of Traffic Control System Under Cyberattacks with Falsified Data

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Abstract

Existing traffic control systems are mostly deployed in private wired networks. With the development of wireless technology, vehicles and infrastructure devices will be connected through wireless communications, which might open a new door for cyberattackers. It is still not clear what types of cyberattacks can be performed through infrastructure-to-infrastructure and vehicle-to-infrastructure communications, whether such attacks can introduce critical failure to the system, and what the impacts are of cyberattacks on traffic operations. This paper investigates the vulnerability of traffic control systems in a connected environment. Four typical elements, including signal controllers, vehicle detectors, roadside units, and onboard units, are identified as the attack surfaces. The paper mainly focuses on attacking actuated and adaptive signal control systems by sending falsified data, which is considered as an indirect but realistic attack approach. The objective of an attacker is to maximize system delay with constraints such as budget and attack intensity. Empirical results show that different attack scenarios result in significant differences in delay, and some ineffective attacks may even improve the system performance. Simulation results from a real-world corridor show that critical intersections, which have a higher impact on network performance, can be identified by analyzing the attack locations. Identification of such intersections can be helpful in designing a more resilient transportation network.

Existing transportation infrastructure is usually isolated regarding connectivity as all vehicles are operated independently, and traffic control systems are mostly deployed in a private wired network. With the development of wireless technology, vehicles and infrastructure will be connected through wireless communications [e.g., Dedicated Short Range Communication(DSRC) or cellular network], which might open a new door for cyberattackers. Cybersecurity of transportation systems has been a growing research area in the past decade, but most efforts are focused on intervehicle communications. As a critical part of the transportation infrastructure, existing traffic control systems have a profound impact on the safety and efficiency of urban traffic flow, but are very vulnerable to cyberattacks because of the “systematic lack of security consciousness” (1). For example, an Argentinian security expert hacked into New York City’s wireless vehicle detection system with a cheap wireless device. The vulnerabilities he found allowed anyone to take complete control of the devices and send fake data to the traffic control systems (2). Although traffic signals were not directly controlled, fake vehicle data could cause severe traffic congestion and increase crash risks. Another example involved hacking into a variable message sign in Austin, Texas, and displaying “Zombie Ahead” instead of

correct traffic information (3). To systematically investigate the cybersecurity of transportation infrastructure, the NCHRP started a new project to develop guidance for transportation agencies on mitigating the risks from cyberattacks toward traffic management systems (4).

However, it is still not clear what types of cyberattacks can be performed through infrastructure-to-infrastructure (I2I) and vehicle-to-infrastructure (V2I) communications, whether such attacks can create critical failure to traffic control systems, and what are the impacts of cyberattacks on traffic operations. A systematic study of the vulnerabilities of the existing traffic control system and corresponding remedies needs to be established. The objective of this paper is to investigate potential attack surfaces and the adversarial consequences such attacks may bring to the traffic network.

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First, four possible attack surfaces of the traffic control system in a connected environment are identified, including signal controllers, vehicle detectors, onboard units (OBUs), and roadside units (RSUs). The focus of analysis is on attacking actuated and adaptive signal control systems by sending falsified data from either hacked vehicle detectors or compromised OBUs. The attack is modeled as an optimization problem with the objective to maximize system delay and constraints, such as the number of compromised devices and attack intensity. Analysis of a hypothetical intersection shows that some attacks are effective in increasing total delay, whereas others are not. Finally, a real-world corridor is used to evaluate the proposed attack methods.

The rest of this paper is organized as follows. The second section provides a brief review of related work. In the third section, four attack surfaces with different attack strategies are identified. The fourth section presents the traffic model to represent the vehicle dynamics and the attack model. The fifth section evaluates the effectiveness of different attack strategies at a hypothetical intersection and a real-world corridor. The final section gives the conclusions and outlines the directions of future work.

Related Work

In this section, a brief overview of cybersecurity-related transportation infrastructure studies is provided. Ghena et al. analyzed the security of a currently deployed traffic signal control system and found the controller network could be infiltrated through its wireless infrastructure (1). Once on the network, the controller could be accessed by the operating system's debug port or through National Transportation Communications for ITS Protocol (NTCIP) commands. Although the safety of the signal operations was protected by the Malfunction Management Unit (MMU), the attackers could generate inefficient signal timing plans that might cause traffic congestion and even denial of service. This study mainly demonstrated how to leverage existing design flaws to gain control of the signal system, but didn't provide detailed attack strategies and corresponding consequences.

Laszka et al. (5) and Ghafouri et al. (6) studied the vulnerability of fixed-time signal control to cyberattacks. The attacks were formulated as mathematical programming problems with different objectives such as worst-case network accumulation, worst-case lane accumulation, and risk-averse target accumulation. Heuristic and decomposition algorithms were implemented to solve the problem at a network level. A precondition of tampering fixed-time signal control is that the attacker can access and manipulate signal controller directly. This is not a very realistic assumption unless the attacker can access the traffic signal cabinet physically. However, it is much easier to falsify input data to influence the control decisions under actuated or adaptive control. Toward this end, Jeske investigated Google and Waze navigation systems and demonstrated how attackers could take control of the navigation system and influence the traffic

flow by sending false location information (7). Tufnell successfully hacked into Waze maps and generated fake GPS coordinates to create virtual traffic jams (8). However, neither of the two studies incorporated the fake data into traffic control systems and analyzed the consequences.

Other than tampering with traffic signal operations, Reilly et al. presented a study on attacking freeway ramp metering to generate arbitrarily complex congestion patterns (9). Finite-horizon optimal control and multiobjective optimization techniques were used to launch attacks on coordinated ramp metering controllers. Different attack scenarios were designed and conducted. Results showed that arbitrary congestion-on-demand patterns could be created with enough controlled ramps.

Although how to detect and protect the system from cyberattacks is beyond the scope of this paper, some approaches have been proposed to detect anomaly from traffic-flow patterns. For example, Canepa and Claudel tried to detect falsified probe-based vehicle data using the Lighthill-Whitham-Richards (LWR) traffic-flow model (10). The detection was posed as a mixed integer linear feasibility problem. Zhang et al. quantified anomaly by proposing an anomaly index in both spatial and temporal perspectives, founded on dictionary-based compression theory (11). The original intention was to identify non-recurrent traffic-flow pattern caused by incidents, but this method could be potentially used to detect cyberattacks and design defense strategies.

Threat Model

Before presenting the attack model, the threat model of a "connected" intersection is introduced and shown in Figure 1. Here, "connected" refers to that the intersection and vehicles are equipped with wireless communication devices (such as RSUs and OBUs) and can communicate with each other. Whereas exact deployments are different from location to location, we consider four typical elements in the traffic control system as possible attack surfaces:

- Traffic signal controller: used to generate signal timing plans based on different control strategies, including fixed-time, actuated and adaptive strategies. If traffic signals are under actuated or adaptive control, the controller utilizes data from vehicle detectors and RSUs to make control decisions.
- Vehicle detectors: used to detect vehicles and generate service calls to signal controller. If vehicle detectors are configured as system detectors, they can also be used to provide volume and speed information.
- OBUs in vehicles: used to generate vehicle-related information [e.g., basic safety messages (BSMs)] and broadcast the information to other vehicles and infrastructure through over the air messages.
- RSUs at intersections: used to broadcast infrastructure-related messages (e.g., Signal Phasing and

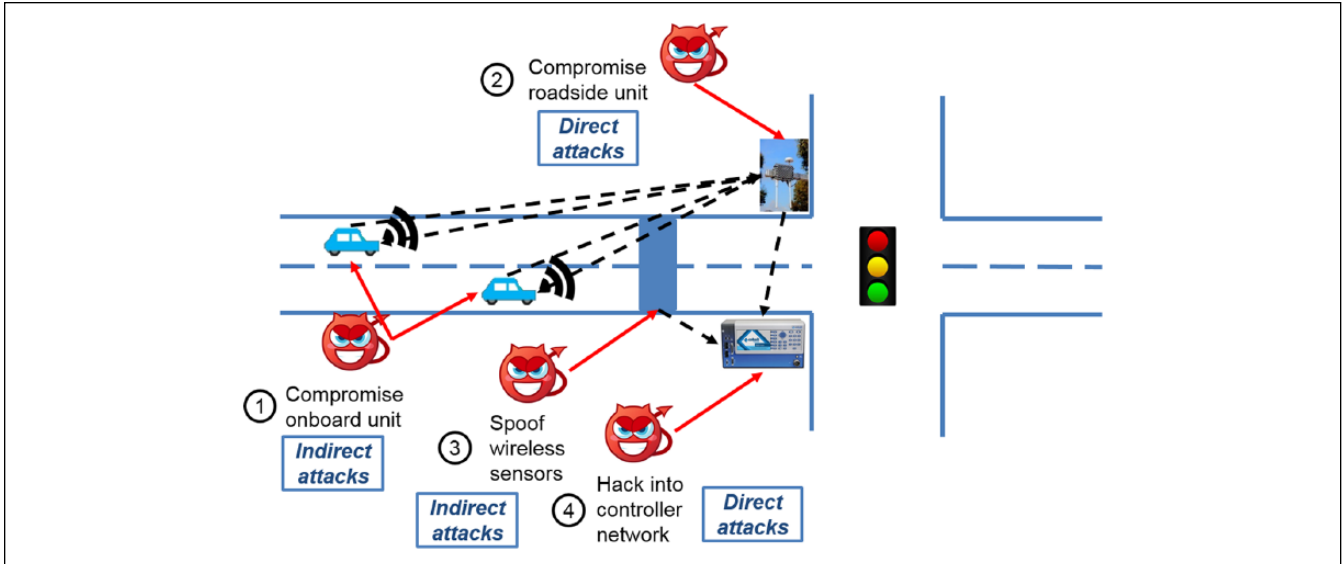


Figure 1. Intersection threat model.

Timing (SPaT), and MAP) and receive vehicle information. It provides input data (e.g., trajectory) to signal controller.

Based on the attack surfaces, two types of attacks are identified: direct attack and indirect attack. Direct attack refers to hacking into the signal controller and RSU and changing the signal timing plans directly. To launch direct attacks, an attacker needs physical access to the devices, which requires the attacker to open the signal controller cabinet and connect to the signal controller or the RSU using an Ethernet cable. Indirect attack refers to tampering with data from vehicle detectors and OBUs. Usually, only part of the input data can be falsified. Indirect attacks are more realistic to conduct. For example, spoofing into wireless vehicle detectors (2), or compromising OBUs in private vehicles. This paper focuses on indirect attacks under actuated and adaptive signal control. For actuated signal control, it is assumed that the signal controller utilizes vehicle detector data to perform actuation logic. Compromised vehicle detectors may generate fake vehicle calls or cancel real vehicle calls. For adaptive signal control, it is assumed that the signal controller generates optimal signal plans based on BSM data from connected vehicles (CVs). Compromised OBUs may insert virtual vehicles on the roadway that don't exist.

Traffic And Attack Models

To model the transportation network and quantify the consequences of cyberattacks, a traffic-flow model is needed. The cell transmission model (CTM) (12, 13) is applied for two reasons. The CTM is a macroscopic traffic model that can be used to simulate network traffic with thousands of vehicles and attack scenarios in an efficient way. However, compared

with other link-based flow and density models, CTM divides roadway into homogeneous segments, so that attacks can be launched at different locations (cells). This section first introduces how to model actuated and adaptive signal control with CTM, and then presents the attack model.

Cell Transmission Model

CTM is a first-order approximation to LWR partial differential equation. The model assumes a triangular fundamental diagram and discretizes space into homogeneous cells and time into intervals. The cell length is equal to one-time interval multiplied by free-flow speed defined in the fundamental diagram. CTM was originally developed to model highway traffic with a single entrance and exit (12). Later, the model was extended to represent network traffic, which allows it to model traffic flows at signalized intersections (13). A typical intersection in CTM is shown in Figure 2.

There are six types of cells: ordinary cell, merging cell, diverging cell, intersection cell, source cell, and sink cell. An ordinary cell has one preceding cell and one following cell, and has limited jam density and capacity. A merging cell has multiple preceding cells and one following cell, whereas a diverging cell has one preceding cell and multiple following cells. An intersection cell is similar to an ordinary cell, except that the flow is controlled by signal timing. Source cells and sink cells are responsible for generating and exiting vehicles. Due to space limitation, for the detailed formulation of CTM, refer to (12, 13).

The parameters of the CTM model in this paper are configured as follows. Free-flow speed v is set to 54 km/h (15 m/s). Backward shockwave speed w is set to 18 km/h (5 m/s). The maximum flow rate Q_m is set to 1800 vph and the corresponding critical density k_m is 33.33 vpkm and jam density

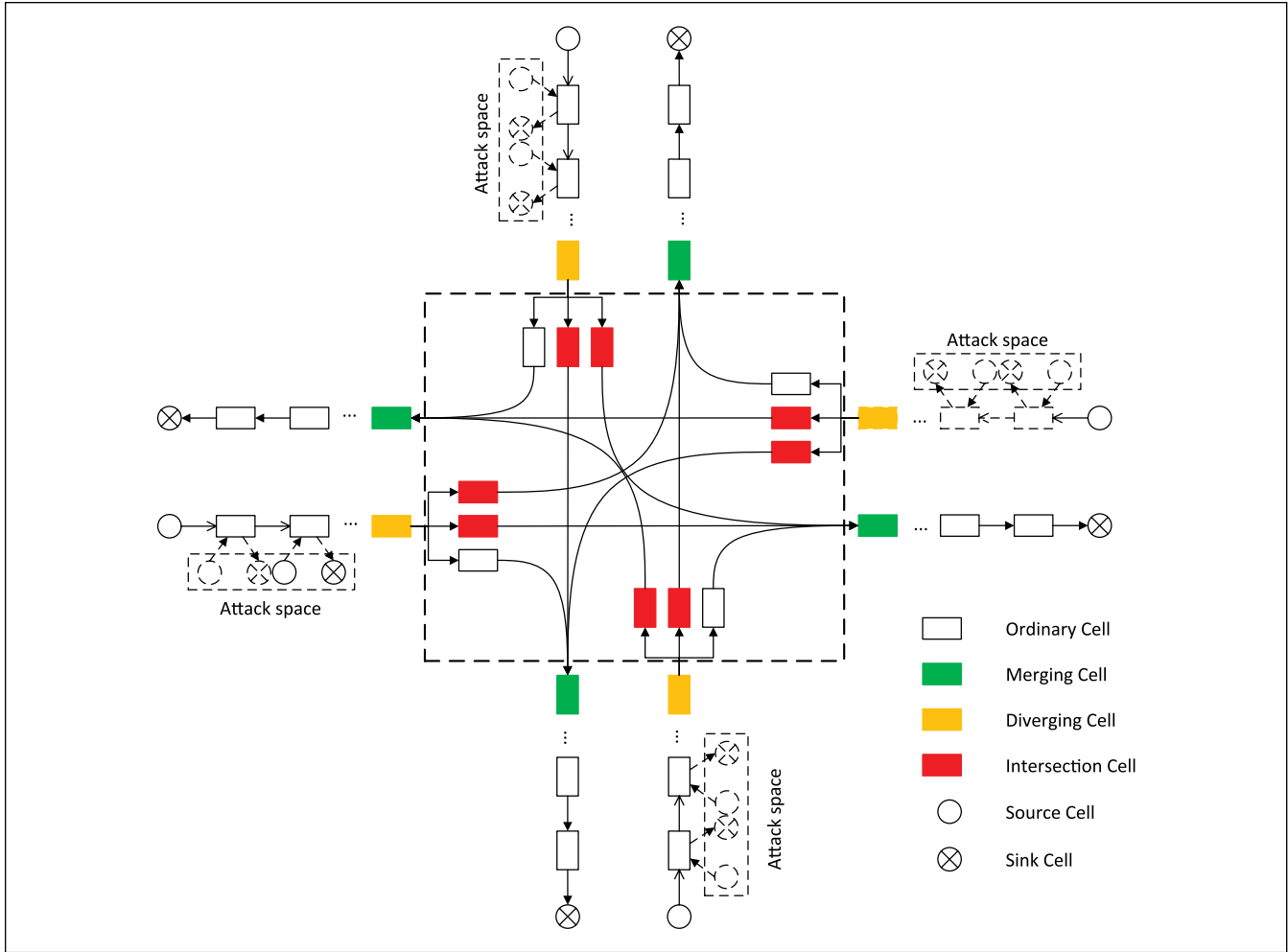


Figure 2. Intersection representation of CTM with attack spaces.

k_j is 133.33 vpk. Time step is set to 2 s, which is similar to the unit extension time in actuated control. As a result, the cell length is 30 m.

Model Actuated Signal Control with CTM. To model actuated signal control with CTM, it is assumed that stop-bar detectors are installed in intersection cells. The density ratio of cell i at time t can be calculated as $d(i,t) = n(i,t)/N(i)$, where, $n(i,t)$ is the number of vehicles in cell i at time t , and $N(i)$ is the maximum number of vehicles in cell i . A critical density ratio d_c is defined for each intersection cell. The actuation logic is modeled based on d_c . If the density ratio of intersection cell i at time t is less than the critical density ratio, then the current phase is terminated. Otherwise, extend green to the next time step.

To determine the best d_c , a series of simulations with different values of d_c were run. Vehicle delay in cell i at time t is defined as the difference between $n(i,t)$ and the number of vehicles that can be discharged from the cell $y(i,t)$, because in CTM vehicles are either in free-flow speed (discharged to the following cell) or in queuing state (remained in current cell):

$$D = \sum_{t \in T} \sum_{i \in I} [n(i,t) - y(i,t)]. \quad (1)$$

Results show that both lower and higher critical density ratios generate higher vehicle delay. Lower critical density ratios correspond to longer unit extension times whereas higher critical density ratios correspond to shorter unit extension times. The lowest delay occurs when $d_c = 0.25$, which is the critical density ratio ($k_m/k_j = 0.25$) that separates free-flow and congestion regime. For a vehicle actuation logic, it is appropriate to terminate green when the traffic state changes from congested to free flow. Therefore, $d_c = 0.25$ is used in numerical experiments.

Model Adaptive Signal Control with CTM. The adaptive control algorithm is adapted from Sen and Head (14) and Feng et al. (15). Signal optimization is formulated as a dynamic programming (DP) problem, in which each phase is considered as one stage in DP. A forward recursion is used to calculate performance measures and record optimal value function.

The objective of the forward recursion is to choose an optimal signal plan with minimal total vehicle delay. A backward recursion is used to retrieve the optimal solution.

The major difference of the algorithm applied in this study from the original algorithm is the performance function calculation. In previous DP formulations, the performance measures were calculated from an arrival table that included estimated time of arrival and requested phase of each vehicle. However, CTM is a macroscopic model in which individual vehicle information is not available. To accurately calculate vehicle delay, a snapshot of the current network condition is taken at the beginning of each signal optimization. A parallel CTM simulation is executed based on the snapshot as an initial network condition to generate vehicle delays in each DP iteration.

The signal optimization algorithm plans as many stages (phases) as necessary until all vehicles in the snapshot pass the intersection cells. A rolling horizon scheme is adopted in which the optimization is performed at the beginning of each phase to include recent vehicle arrivals.

Attack Model

It is assumed that an attacker has limited resources. For example, the number of vehicle detectors that can be tampered with, or the number of OBUs that can be compromised are limited. As a result, an attacker needs to choose a subset of locations or devices to maximize the profit, which is defined as maximization of network congestion. Formally, an attack A is defined as

$$A = (S, \{n'(i, t) | \forall i \in S\})$$

where S is the set of cells can potentially be under attack and $n'(i, t)$ is the number of vehicles in the cell under attack. Attacks are conducted through increasing or decreasing number of vehicles in a cell to mimic the change of stop-bar detector data and BSM distribution.

The attack model can be expressed as

$$\max_A D(A) \quad (2)$$

s.t.

$$|S| \leq B \quad (3)$$

$$n'(i, t) \leq \min(n(i, t) + \varepsilon, N(i)), \forall i \in S \quad (4)$$

$$n'(i, t) \geq \max(n(i, t) - \varepsilon, 0), \forall i \in S \quad (5)$$

The objective function means an attacker intends to maximize total vehicle delay. The first constraint indicates that the attacker is limited by budget B . The next two constraints represent the cautiousness of the attacker. The number of vehicles can be changed, is limited by a threshold ε and the

physical limits of the road. If the data deviate a lot from the normal range, the attacker can be easily detected by the defender.

Numerical Examples

In this section, numerical results based on a hypothetical intersection, and insights on the effectiveness of the attacks are presented first. Then a real-world six-intersection corridor in Ann Arbor, MI, is built to evaluate the attack models. All models are coded in Matlab.

A Hypothetical Intersection

The layout of a hypothetical intersection is shown in Figure 2. This is a typical four-leg intersection with all vehicle movements. There are four signal phases: eastbound and westbound left turn (Phase 1), eastbound and westbound through (Phase 2), northbound and southbound left turn (Phase 3), and northbound and southbound through (Phase 4). Right-turn vehicles are not restricted by traffic signals. The minimum green time is set to five time steps (10 s) and the maximum green time is set to 20 steps (40 s) for each phase. The length of each approach is 10 cells (including the intersection cells), which is similar to the DSRC communication range. Traffic demand is set to 1,000 vph eastbound/westbound and 800 vph northbound/southbound. Vehicle arrivals follow the Poisson distribution. Turning ratios of each approach are the same and set to 0.2/0/7/0.1 for left turn, through, and right turn respectively. Simulation runs for 1,000 time steps with 100 steps as a warm-up period.

Figure 3 shows the total delay and congestion pattern of eastbound approach under actuated and adaptive control without attacks. This serves as the baseline for our comparison. Different colors represent different congestion levels, with green being no congestion and red being the severest congestion.

Attack Under Actuated Control. Under actuated control, it is assumed that stop-bar detector data can be manipulated by the attacker so that the number of vehicles at intersection cells can be added (generate fake vehicle calls) or subtracted (cancel real vehicle calls). This results in two attack modes $M = 2$. To cause maximum damage, the attacker changes the detector data as much as possible, but within the threshold $\varepsilon = 0.5$. Then $n'(i, t)$ is equal to either $\min(n(i, t) + \varepsilon, N(i))$ or $\max(n(i, t) - \varepsilon, 0)$. The budget B is set to 4 so that all phases can be attacked. To thoroughly analyze the effectiveness of all attack scenarios, all the possibilities are enumerated, which results in 80 different cases:

$$\sum_{p=1,2,3,4} C_p^p * M^p = 80 \quad (6)$$

where p is the signal phase index, and P is the total number of phases.

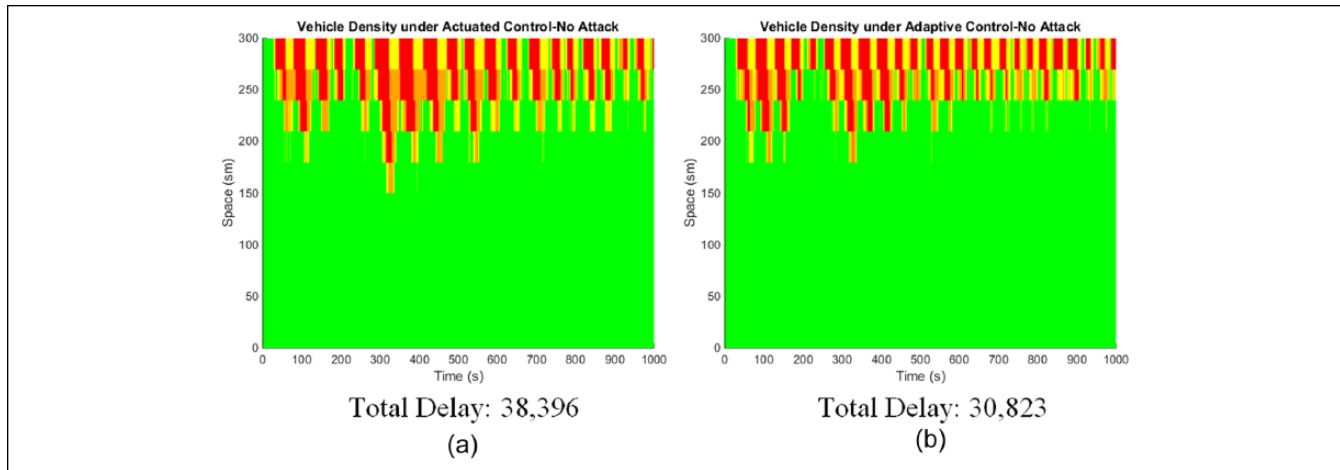


Figure 3. Vehicle delay comparison without attack: (a) actuated control (left) and (b) adaptive control (right).

Figure 4 shows total vehicle delay and average total delay by the number of attacking phases. It can be seen from Figure 4a that the effectiveness of different attacks varies a lot. Figure 4b shows the trend that attacks cause more vehicle delay when the number of attacking phases increases.

Figure 5 shows the comparison between the most effective attack and least effective attack at the eastbound approach. The most effective attack occurs when Phases 2, 3 and 4 are under attack, with subtracting vehicles at intersection cells corresponding to Phase 2, and adding vehicles at intersection cells corresponding to Phases 3 and 4. The resultant total delay can be six times higher than the baseline scenario. The least effective attack occurs when attacking intersection cells related to Phases 1 and 3, with subtracting vehicles on both phases. The resultant total delay (36,441) is even smaller than the baseline scenario (38,396), which indicates that the attack improves the system performance. The reason is that actuated control is not the optimal control strategy. In certain cases, when a phase is green with lower demand while other phases are red with higher demand, it is more efficient to terminate the lower demand phase earlier to serve other phases. In this case, Phases 1 and 3 are left-turn phases with lower demand. Subtracting vehicles shortens both phases, which gives more time to higher demand Phases 2 and 4.

Attack Under Adaptive Control. Under adaptive control, the control algorithm utilizes data from CVs (e.g., BSMs) to generate optimal signal plans, so that every cell within the communication range can be potential targets. It is assumed that an attacker is only interested in manipulating the number of vehicles in ingress cells because vehicles in egress cells don't affect the signal optimization. The attacker can add or subtract vehicles at a different number of approaches with the maximum number of attacking approaches $A = 4$. If the attacker decides to attack one approach, then all ingress cells

on that approach are affected. The threshold ε is also set to 0.5. In total, 30 attack scenarios are generated.

Figure 6 shows the total vehicle delay of all attack scenarios and the average total delay by the number of attack approaches. Figure 6a compares the total delay of adding vehicles or subtracting vehicles when attacking the same approach(es). In general, adding fake vehicles is more effective than removing real vehicles. Under current demand level (medium), green time wasted under longer cycle lengths can cause more delay than increased percentage of lost time with shorter cycle lengths. Figure 6b shows a similar pattern: the average total delay increases with the number of attack approaches.

Another finding is that attacks under adaptive control are far less effective than under actuated control with the same attack intensity ε . The most effective attack under adaptive control causes a 41,199s of total vehicle delay, which is only 33.66% more than the baseline scenario. However, the most effective attack under actuated control generates a delay of six times more than the baseline scenario. Under adaptive control, all ingress cells (including intersection cells) are affected, whereas under actuated control, only intersection cells are affected. However, results suggest that adaptive control is more robust than actuated control. Because adaptive control tries to minimize total delay under the impact of attacks, based on inputs from all ingress cells, whereas actuated control logic can only accommodate instantaneous arriving flow at intersection cells, but doesn't have an overall picture of the current traffic condition.

Plymouth Road Corridor

Six consecutive intersections along Plymouth Road at Ann Arbor, MI, are modeled in CTM to evaluate the attack model under actuated control. To calibrate the model, video data were collected on May 16, 2017, from 4:00 to 5:00 p.m. Traffic volume of each approach, turning ratio of each

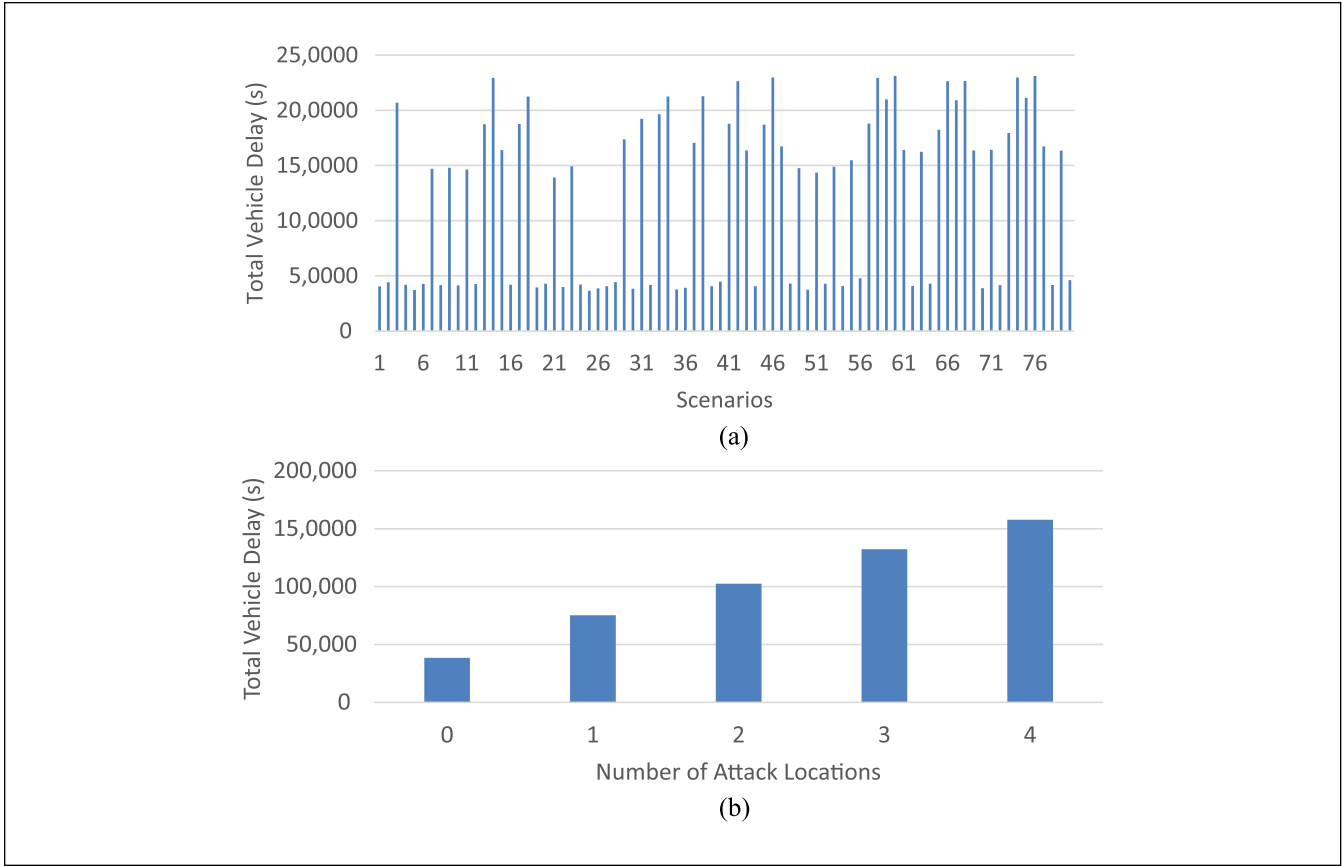


Figure 4. Vehicle delay by attack scenarios and number of attacking phases (actuated control): (a) vehicle delay under all attack scenarios (top) and (b) average total vehicle delay by number of attacking phases (bottom).

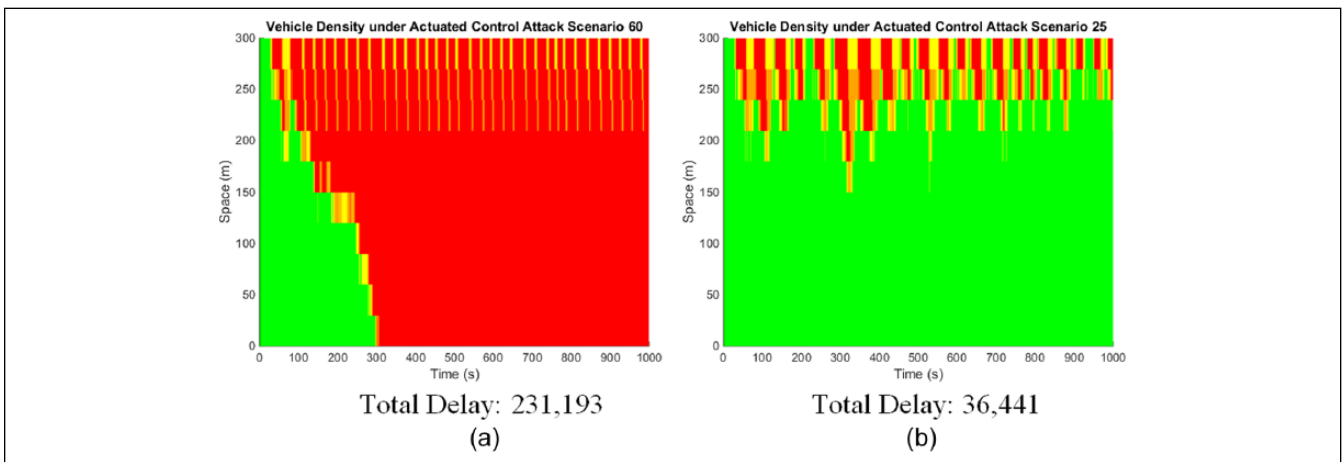


Figure 5. Comparison between the most effective attack and the least effective attack: (a) most effective attack (left) and (b) least effective attack (right).

movement, and signal timing of each intersection were extracted from the video and used as input to the CTM model.

The corridor contains two T-shape intersections and four standard intersections. The standard intersections have four phases as defined in the previous section, whereas the T

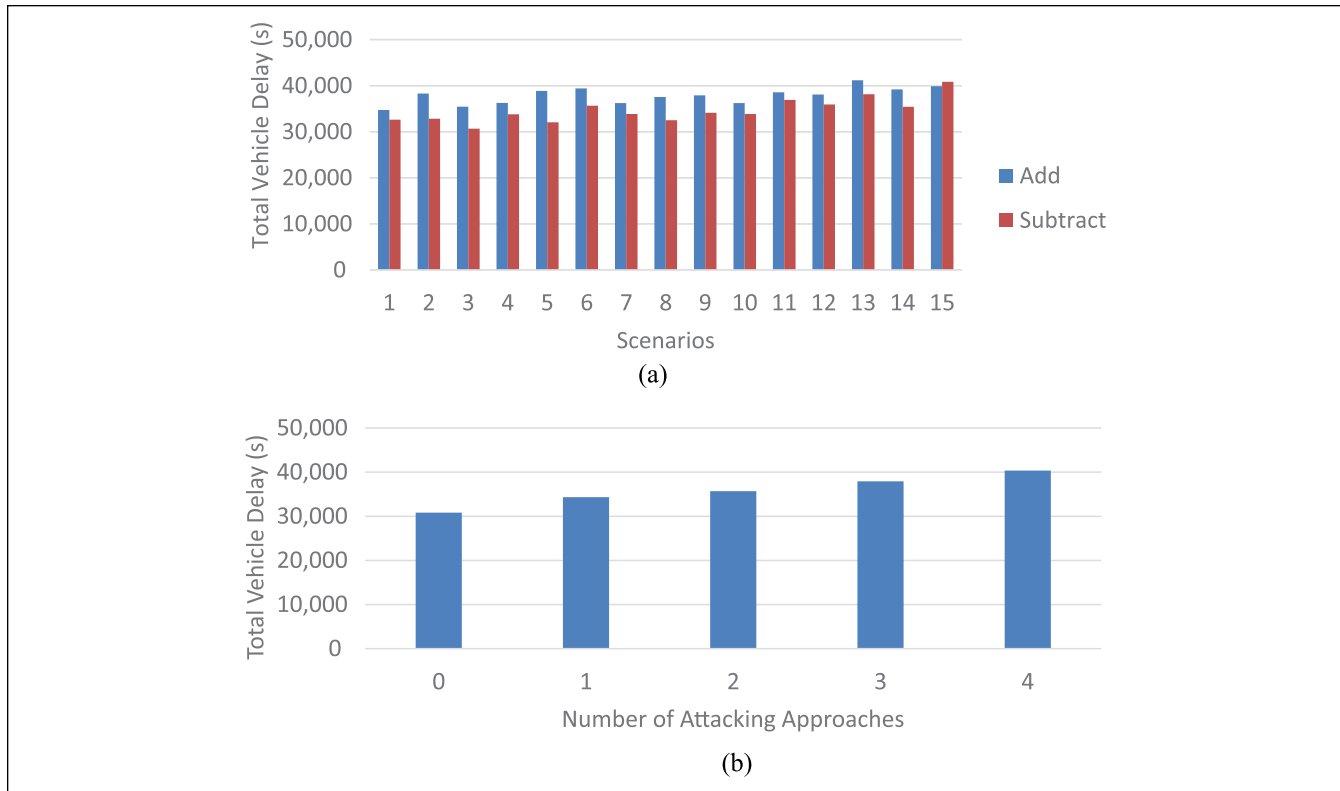


Figure 6. Vehicle delay by attack scenarios and number of attacking approaches (adaptive control): (a) vehicle delay under all attack scenarios (top) and (b) average total vehicle delay by number of attacking approaches (bottom).

intersections have only two phases. Therefore, there are 20 signal phases along the corridor. Each is identified as a potential attack location. The minimum and maximum green time for the through movement along Plymouth Road is set to 10 and 30 time steps, whereas the rest of the phases have 5 and 15 time steps for minimum and maximum green time respectively. Each attack scenario lasts 2,100 time steps, which contains 300 time steps of warm-up (no attack) period and 1,800 time steps for performance evaluation (under attack). It is assumed that the attacker has a budget limit so that a maximum of four phases can be attacked. This results in a total number of 87,440 attack scenarios. Due to this large number, the attack scenarios are carried out by Flux, a Linux-based high-performance computing cluster at the University of Michigan. A total of 20 central processing units cores are used to run the attack scenarios in parallel, and the total computation time is about 14 h.

When only one phase is under attack, Scenario 7, which attacks Phase 2 (the through phase on the main arterial) at Intersection 2 by subtracting vehicles, has the highest delay. A snapshot of the corridor at the final simulation time step is shown in Figure 7. The intersection on the left is numbered as 1, and the intersection on the right is numbered as 6. When under attack, the signal controller always terminates Phase 2 on the minimum green time, which causes oversaturation for westbound through traffic and the vehicle queue starts to

accumulate. The queue eventually propagates to Intersection 3 and causes spillover. The spillover prevents westbound through traffic at Intersection 3 from entering the downstream link during green. The through traffic constantly calls for green extensions, which generates more delay for the cross-street traffic because of the long waiting time. The same situation happens when the queue propagates to Intersections 4 and 5. Notice that there is a long queue in the northbound approach of Intersection 5 because this approach has heavy left-turn traffic. The spillover on the main arterial prevents vehicles turning left from the cross street. The result indicates that Phase 2 at Intersection 2 is the critical phase along the corridor.

Figure 8 shows vehicle delay under all attack scenarios with a different number of attacking phases. The average total vehicle delay increases with the number of attacking phases, which is consistent with previous results. If all four phases are under attack, the most effective way is to subtract vehicles from Phase 2 (through movement on Plymouth Road) at Intersection 2, and Phase 3 (left-turn phase on cross street) at Intersection 6, at the same time adding vehicles to Phase 3 at Intersection 2, and Phase 2 at Intersection 6.

Although trying all attack scenarios guarantees the optimal solution, it is unrealistic for an attacker to enumerate all the possibilities and find the best strategy in real time. Thus, a simple greedy attack policy is implemented to find an

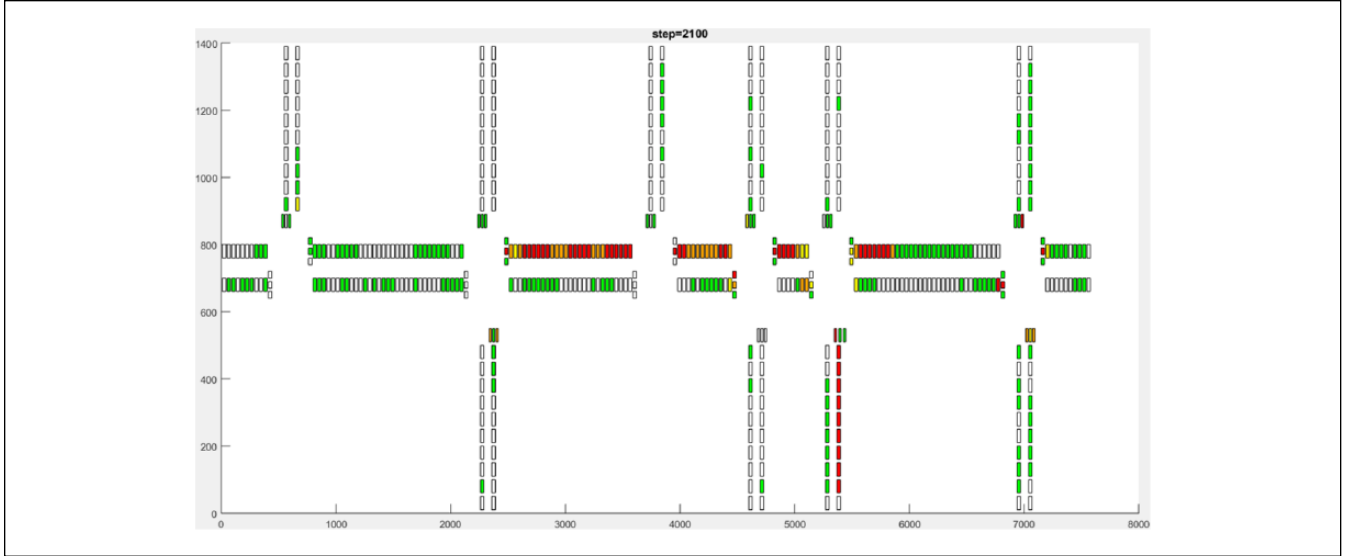


Figure 7. Snapshot of the corridor at the final simulation step.

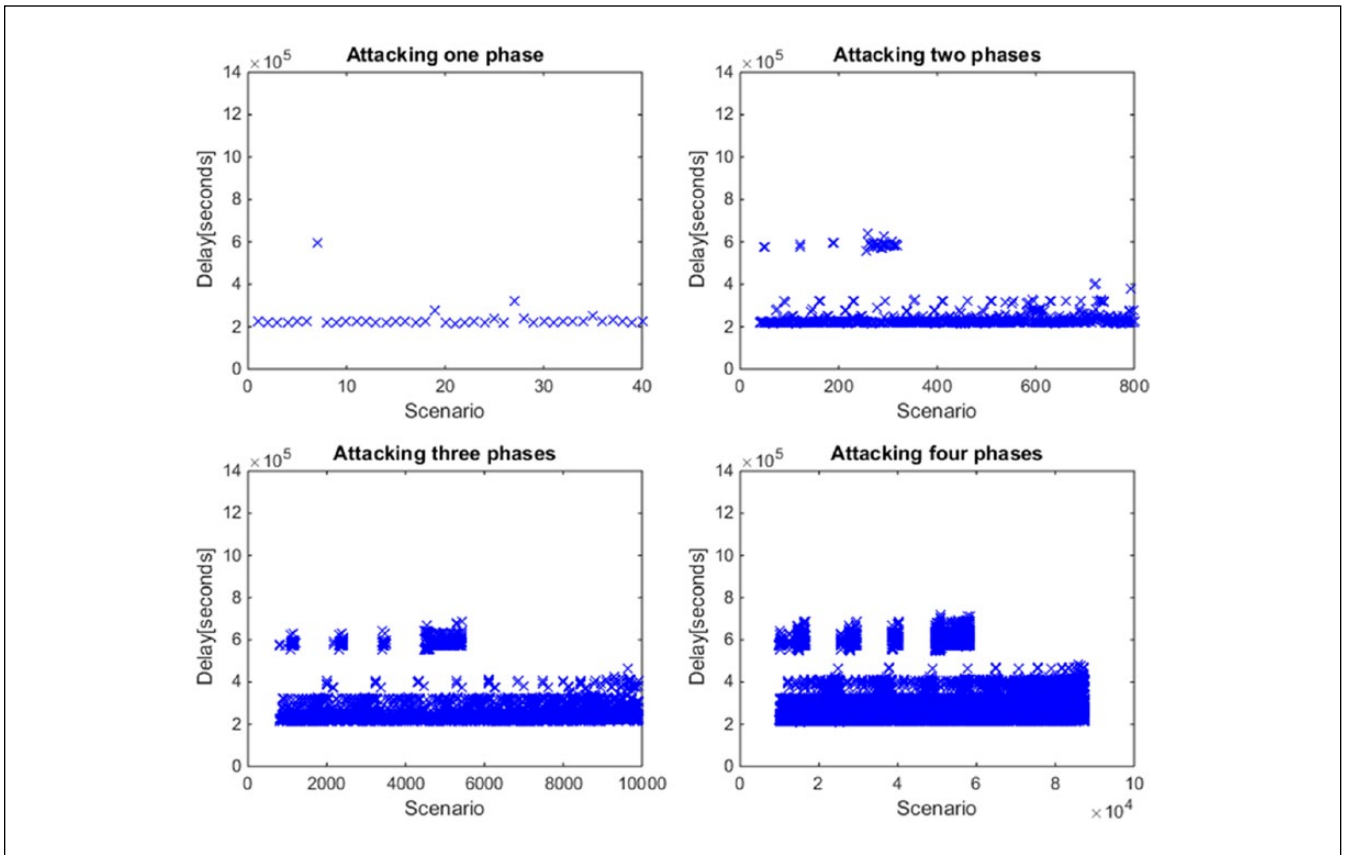


Figure 8. Vehicle delay under all attack scenarios.

effective attack strategy. The attacker starts with attacking one phase and enumerates all the scenarios to find the critical phase that causes the highest delay. Given the previous attacking phase, the attacker adds another phase and again

enumerates all possibilities to find the second critical phase. This process is repeated until the budget (maximum number of phases) limit is reached. Take Plymouth corridor as an example: the total number of scenarios needed to be

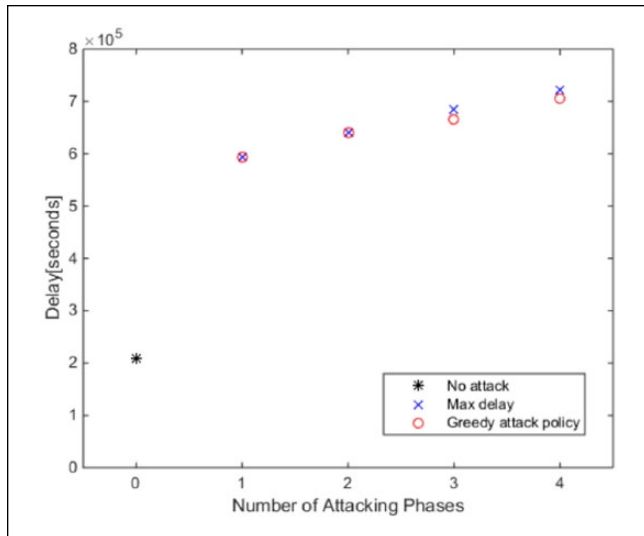


Figure 9. Comparison between enumeration and greedy attack policy.

simulated by the greedy attack policy is $40 + 38 + 36 + 34 = 148$, assuming the budget is four phases. This number is significantly smaller than the total number of scenarios by enumeration. The maximum delay generated by the greedy attack policy is shown in Figure 9, as well as the delay from optimal attack strategy by enumeration. When only one or two phases are under attack, the attack strategies found by the greedy attack policy are the same as the optimal attack strategy. When more phases are under attack, the greedy attack policy can still find an attack strategy that is very close to the optimal solution, within much less time.

Conclusion and Further Research

This paper investigated the vulnerabilities of traffic control systems under cyberattacks. It focused on attacking actuated and adaptive signal control systems by sending falsified data to influence signal timing plan generation. The primary goal of an attacker was to maximize networkwide vehicle delay, with constraints such as budget and attack intensity. Results from a hypothetical intersection showed that some attacks could be very effective and cause severe congestion, whereas others may even reduce the total delay. Results from a real-world corridor showed that critical intersections, which had a higher impact on congestion, can be identified by analyzing the attack locations. Identification of critical intersections would be helpful in designing a more resilient transportation network.

To launch attacks, an attacker needs to collect necessary information about the signal control system, such as phase sequence, minimum green time and maximum green time, and so forth. However, this paper focuses mainly on the consequences of the traffic systems under cyberattacks. The authors will explore other steps in the

end-to-end exploitation, for example, reconnaissance, in future work. Moreover, the authors will extend the current results toward two directions. First, besides maximizing total delay, attackers may have other objectives, such as obtaining personal gain (e.g., minimizing personal delay) or creating safety risks (e.g., causing more vehicles in dilemma zone). With different objectives, the attack strategies can be different. Second, it is necessary to consider the cybersecurity problem from a defender's point of view. Defense models need to be developed to detect attacks and protect the transportation infrastructure.

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References

- Ghena, B., W. Beyer, A. Hillaker, J. Pevarnek, and J. A. Halderman. Green Lights Forever: Analyzing the Security of Traffic Infrastructure. Presented at 8th USENIX Conference on Offensive Technologies, Berkeley, Calif., 2014.
- Prigg, M. Has New York's Traffic Light System Been Hacked? *Daily Mail*, May, 2014. <http://www.dailymail.co.uk/sciencetech/article-2617228/New-Yorks-traffic-lights-HACKED-technique-work-world.html>. Accessed Oct. 30, 2017.
- Miller, J. R. Hackers Crack into Texas Road Sign, Warn of Zombies Ahead. *Fox News*, Jan, 2009. <http://www.foxnews.com/story/2009/01/29/hackers-crack-into-texas-road-sign-warn-zombies-ahead.html>. Accessed Oct. 7, 2017.
- Ramon, M. C., and D. A. Zajac. *Cybersecurity Literature Review and Efforts Report*. Prepared for NCHRP Project 03-127 Cybersecurity of Traffic Management Systems. Southwest Research Institute, 2018.
- Laszka, A., B. Potteiger, Y. Vorobeychik, S. Amin, and X. Koutsoukos. Vulnerability of Transportation Networks to Traffic-Signal Tampering. In Proceedings of the Presented at 2016 ACM/IEEE 7th International Conference on Cyber-Physical Systems (ICCPS), Vienna, Austria, 2016.
- Ghafouri, A., W. Abbas, Y. Vorobeychik, and X. Koutsoukos. Vulnerability of Fixed-Time Control of Signalized Intersections to Cyber-Tampering. Presented at 2016 Resilience Week (RWS), Chicago, USA, 2016.
- Jeske, T. Floating Car Data from Smartphones: What Google and Waze Know about You and How Hackers Can Control Traffic. Presented at BlackHat Europe, Amsterdam, Netherlands 2013.
- Tufnell, N. Students Hack Waze, Send in Army of Traffic Bots. *Wired*, 2014. <http://www.wired.co.uk/article/waze-hacked-fake-traffic-jam>. Accessed Feb. 11, 2018.
- Reilly, J., S. Martin, M. Payer, and A. M. Bayen. Creating Complex Congestion Patterns via Multi-Objective Optimal Freeway Traffic Control with Application to Cyber-Security. *Transportation Research Part B: Methodological*, Vol. 91, 2016, pp. 366–382. <https://doi.org/10.1016/j.trb.2016.05.017>.
- Canepa, E. S., and C. G. Claudel. Spoofing Cyber Attack Detection in Probe-Based Traffic Monitoring Systems Using

- Mixed Integer Linear Programming. Presented at 2013 International Conference on Computing, Networking and Communications (ICNC), San Diego, USA, 2013.
11. Zhang, Z., Q. He, H. Tong, J. Gou, and X. Li. Spatial-Temporal Traffic Flow Pattern Identification and Anomaly Detection with Dictionary-Based Compression Theory in a Large-Scale Urban Network. *Transportation Research Part C: Emerging Technologies*, Vol. 71, 2016, pp. 284–302. <https://doi.org/10.1016/j.trc.2016.08.006>.
 12. Daganzo, C. F. The Cell Transmission Model: A Dynamic Representation of Highway Traffic Consistent with the Hydrodynamic Theory. *Transportation Research Part B: Methodological*, Vol. 28, No. 4, 1994, pp. 269–287. [https://doi.org/10.1016/0191-2615\(94\)90002-7](https://doi.org/10.1016/0191-2615(94)90002-7).
 13. Daganzo, C. F. The Cell Transmission Model, Part II: Network Traffic. *Transportation Research Part B: Methodological*, Vol. 29, No. 2, 1995, pp. 79–93. [https://doi.org/10.1016/0191-2615\(94\)00022-R](https://doi.org/10.1016/0191-2615(94)00022-R).
 14. Sen, S., and K. L. Head. Controlled Optimization of Phases at an Intersection. *Transportation Science*, Vol. 31, No. 1, 1997, pp. 5–17.
 15. Feng, Y., K. L. Head, S. Khoshmagham, and M. Zamanipour. A Real-Time Adaptive Signal Control in a Connected Vehicle Environment. *Transportation Research Part C: Emerging Technologies*, Vol. 55, 2015, pp. 460–473. <https://doi.org/10.1016/j.trc.2015.01.007>.
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