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A game-theoretic analysis of DoS attacks on driverless vehicles

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arXiv:1902.09590v1 [cs.GT] 25 Feb 2019

***Abstract*—Driverless vehicles are expected to form the foundation of future connected transport infrastructure. A key weakness of connected vehicles is their vulnerability to physical-proximity attacks such as sensor saturation attacks. It is natural to study whether such attacks can be used to disrupt swarms of autonomous vehicles used as part of a large fleet providing taxi and courier delivery services. In this paper, we start to examine the strategic options available to attackers and defenders (autonomous-fleet operators) in such conflicts. We find that attackers have the upper hand in most cases and are able to carry out crippling denial-of-service attacks on fleets, by leveraging the inherent deficiencies of road networks identified by techniques from graph analysis. Experimental results on ten cities using real-world courier traces shows that most cities will require upgraded infrastructure to defend driverless vehicles against denial-of-service attacks. We found several hidden costs that impact equipment designers and operators of driverless vehicles — not least, that road-networks need to be redesigned for robustness against attacks thus raising some fundamental questions about the benefits.**

I. Introduction

The area of driverless vehicles has seen rapid developments in the last few years. Substantial industrial investment in driverless technology has been made in the wake of recent advances in sensing and computational control systems. While the transformative impact of such automation has been recognised, the trust implications of their deployment have yet to be adequately discussed.

While driverless vehicles were conceived nearly a century ago, it was not until the application of statistical machine learning combined with control automation, that the ideas crystalised into reality. Therefore it is natural to ask whether it is possible to apply adversarial statistics to also disrupt fleets of driverless vehicles at scale. In the context of fleets, we are concerned about the availability of driverless as the key security property, followed by authenticity of control, integrity, and lastly confidentiality of information. Our key concern is availability, because it is the most easily influenced property — an attacker who jams the optical and acoustic channels can induce an emergency stop resulting in a denial-of-service attack. The question however is, can this be done at scale? Our experiments, carried out within the first systematic study of the area, suggest that this may indeed be the case.

Driverless vehicles collect sensory input via lidars, radar, visual-range cameras, and ultrasound sensors – all of which are vulnerable to signal saturation attacks [16]. Directional ultrasound acoustic jammers consist of an array of powered ultrasound transducers whose output is focused into a narrow beam with a distance range of a few tens of meters [21]. These were developed with (a short range) for medical imaging and (medium range) for sound entertainment systems [18]. Such precision engineering tools can be repurposed as attack tools to shine an acoustic spotlight to stealthily saturate vehicles deploying sonars. To further compromise safety, an attacker can combine signal saturation with illusion attacks [16]. Illusion attacks cause the information available to the car prior to jamming to be undependable thus causing the vehicle to execute an unsafe stop.

While disabling a single driverless vehicle might not impact the bottom line, doing so at scale certainly will. It is therefore natural to investigate whether individual attacks can be scaled into a service denial attack on an entire fleet of driverless vehicles. We study the robot operator's decision-making behaviour in response to economic costs of service-denial attacks in general (radio jamming, battery exhaustion) with a focus on the behavioural aspects underlying operator response. This paper is not concerned with the fulfillment of security properties (technical jamming attacks and defences) in this paper.

In a real-world scenario, a driverless (fully autonomous) vehicle used to courier packages to customers would stop at the delivery address and alert the recipient. The recipient then walks over to the vehicle, and types in a PIN to retrieve their package. Such driverless cars are expected to be used as part of a last-mile logistics infrastructure to transport people (driverless taxis), deliver packages, and fresh food at strict timelines. These are applications with trustworthiness requirements. Indeed, online super-retailers are hoping their lastmile problem could be solved by a fleet of driverless vehicles they directly control, as opposed to the patchy ecosystem of multiple providers which is the current norm.

As a more theoretical example but one that accurately captures the threat model, consider a courier who has been tasked with delivering bags of cocaine by a dealer. The courier sets up secret appointments to drop off the shipments at pre-determined locations. The courier must select a route visiting all the locations and returning back to the starting point, whilst ensuring minimum expense and maximising safety of the goods. The courier is at risk of attacks from rival dealers who may wish to disrupt delivery, steal goods, or worse. For easier reading, in the rest of the paper, we refer to a driverless vehicle as a *courier*.

We evaluated various attack and defense strategies on 12 different road networks which correspond to popular cities around the world in which driverless courier vehicles are consider viable. We show that in all cases Nash equilibriums exist. However, network effects favour the attackers. Attacks can disrupt an entire fleet of driverless courier vehicles at the scale of a city with just a few of attack units. In some cases the defenses significantly countered an attack strategy, whereas in specific cases, the defense strategy in fact performs worse than if no strategy was employed.

The main contribution of this paper is to develop the first comprehensive analysis of the attack resilience of driverless vehicles to denial-of-service attacks on their sensory input. Instead of analysing specific attacks we develop a generic framework for this purpose: we consider a zero-sum multi-player hider-seeker game where the couriers are the hiders and the attacker coordinates one or more attack units called seekers. The couriers wish to choose optimal routing strategies, that minimise transport time. On the other hand, the attacker aims to choose optimal attack locations to ambush as many couriers as possible. We consider a number of attack and defense strategies motivated by the science of networks, and develop a new understanding of which attack and defense strategies result in stable equilibriums, and the implications of these findings on the hidden costs of a robust infrastructure which is safe for driverless vehicles.

II. Problem description

Consider a courier delivery system where numerous driverless vehicles deliver packages for purchases from an online super-retailer. Once an online order is placed, it is added to the daily schedule of deliveries, called a **tour**, on a fleet of driverless vehicles, individually called a *courier*. This can be represented using a graph $G(V, E)$, where G is the road network with vertex set V corresponding to physical addresses and edgeset E corresponding to roads between them. Each courier starts from the warehouse location $W \in V$ and ends with the warehouse location, with numerous stops at customer delivery locations $C_1, \ldots, C_l \in V$. The goal of the couriers is to optimise both their security and transportation time. Accordingly, each courier, modeling a *hider*, chooses a routing strategy which minimises the probability of attack whilst simultaneously minimising the delivery time (and cost). Each courier's pure strategies are all the possible paths starting from origin through all the destination nodes and returning back to the origin.

The attacker's goal is to *ambush* as many couriers as possible. To achieve this, the attacker positions multiple mobile attack units each modeling a *seeker* on key routes (edges $S \subset E$) of the road network in a coordinated manner, as depicted in figure 1. When an attack unit comes within the physical proximity of a driverless vehicle, it launches a signal-saturation attacks. A signal saturation attack is a class of targeted attacks that focuses on the sensory inputs of a courier vehicle and orchestrates a denial-of-service by jamming the sensor. It can take the form of targeted attacks focusing on one or more of the following: lasers targeting the Lidar or CCD/CMOS (visual camera) sensors, or jamming the GPS, sonar, or other sensory inputs. A successful ambush can

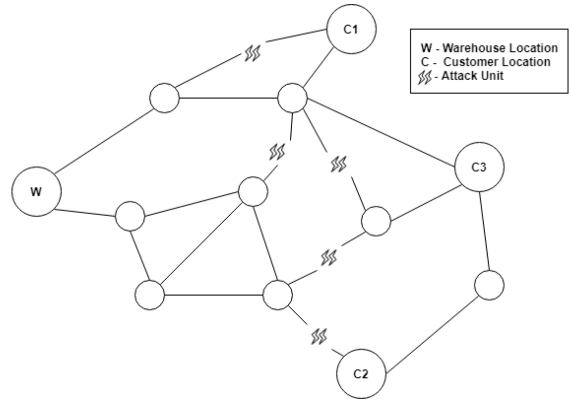


Fig. 1: Multi-party Network Interdiction

result in disabling the courier until it is towed out of the attacker's proximity and possibly rebooted, hence leading to increased delays (transportation time). The attacker's goal is to maximise the amount of delays induced in order to maximise the number of late deliveries. The attacker's pure strategies are all possible combinations of attack resources to edges, thus ${}_{|E|}C_k$ strategies, where $k = |S|$.

Since the attacker has limited resources, they cannot afford to ambush all locations all the time and instead focus on a subset of "ideal" locations. The set of ideal ambush locations corresponds to key routes that are frequented by couriers that are especially useful in achieving the courier's goals. The courier not only wants to minimise transportation time but also ensure their robustness to ambush, thus the courier may chose from a range of routes hoping to avoid ambush on any of their routes.

We can model the above hider-seeker game as a multi-round zero-sum network interdiction game [20]. For a given a road network G, the couriers seek to deliver goods on time whilst hiding from the attacker. The attacker on the other hand is an *interdictor* who aims to interdict (ambush) as many couriers as possible.

Previous researchers [20], [15] considered disruptive attacks on networks to be a single-round game. Such a model is suitable for applications such as a conventional war, in which the attacker has to expend a certain amount of effort to destroy the defender's command, control and communications, and one wishes to estimate how much; or a single epidemic in which a certain amount of resource must be spent to bring the disease under control.

However, where attack and defense co-evolve in an adaptive manner, then we have to consider a multi-round game [11] which has significant explanatory power in many applications. In our scenario, we are specifically interested in the various Nash equilibria that might be possible with pure and mixed strategies.

Each round is consists of two phases, the attack phase and the defence phase. In the attack phase, the attacker deploys attack assets on a subset of links of the network and ambushes any courier they chance upon. The attacker selects edges according to an attack strategy described in Section III-A. The attacker has full information about the roadway graph topology but has no information about the delivery schedules of the couriers.

In the defence phase, the couriers consider the impact of the attack on their delivery efficiency and *adapt* by choosing a defense strategy in accordance with available strategy choice and information. A defense strategy is more efficient if for a given attack strategy, it compels the attacker to increase the number of attack assets to achieve the same level of network disruption.

Similarly, an attack strategy is more efficient, if it either achieves an increase in the number of successful ambushes or forces the defender to expend more resources resulting in deliveries beyond the delivery window.

To quantify attack efficiency, we measure the *percentage increase in late deliveries* induced by the attack as well as the increase in the *delivery-completion time* – i.e the time required to complete deliveries per workday. We then examine the how attack efficiency changes with variance in the delivery window size (the maximum time that can elapse after delivery time, before a delivery is classed as late); the impact of number of attackers on the dynamics of attack-defense strategies.

III. Attacks and defence strategies

We now discuss attack and defense strategies that the players can adopt when playing the multi-round multi-player network interdiction game.

A. Attacks

a) Random edge removal (Baseline): The first attack strategy is the simplest of all, and is one of the most naive attacks. A location is chosen as a suitable site for launching service-denial attacks by choosing an edge from the corresponding graph uniformly at random. This models the case where an attacker has no other information to base their choice and must choose an attack location with no intelligence to hand.

b) Botgrep mincut detection: Thus far, we have established that the mincut size establishes the theoretical upper bound of defence. Therefore it is natural to consider mincut detection techniques as an attack strategy. The traditional description of a mincut from a graph theory perspective, is a partition of the graph into two disjoint subsets that are joined by a small (minimal) number of edges.

Botgrep [12] uses the relative mixing properties of subgraphs to identify edge cuts. Botgrep uses a special probability transition matrix to implement the random walks, where the transition probability between adjacent nodes $i, j \in V$ is $min(\frac{1}{d_i}, \frac{1}{d_j})$, as opposed to $\frac{1}{d_i}$ from i to j in Markovian random walks, where d_i is the degree of node i. Botgrep uses short random walks to instrument mixing time within a partition and to minimise the leakage of walks starting from a partition. It then applies the probabilistic model from SybilInfer to isolate edges which delineate the subset of the graph where mixing speed changes. Thus the output of Botgrep is various graph subsets with different mixing characteristics. The motivation for Botgrep is as follows. While the notion of a **small-cut** is a useful starting point, transport networks may not necessarily contain small-cuts that partition the graph into two or more components that are non-trivial in size. Thus a complimentary approach to small-cut detection is offered by the *Botgrep* technique which combines SybilInfer with machine learning to identify sub-graphs with different mixing characteristics.

c) Infomap cutset detection: Another technique that leverages random walks is Infomap [14]. The intuition underlying Infomap is that the fraction of time spent visiting a node during a random walk can be used to uncover dense subgraphs and the cutsets separating them. Unlike Botgrep which uses short random walks, Infomap uses a few long random walks to sample the graph, and computes node centralities as a function of the number of visits during the random walk. This information is used to search for edge cutsets partitioning the graph using a deterministic greedy search algorithm.

B. Centrality attacks

A second class of attacks uses various measures of node centrality to identify important nodes and proceeds to execute service denial attacks on the node's edges. The intuition underlying these attacks is that attackers often try to disconnect a network by destroying edges of important (central nodes).

a) Degree centrality: The most obvious form of a node's importance is the number of other nodes it is connected to. In this case, the attacker targets edges of high degree nodes by deploying attack resources on as many edges of the highest degree nodes whilst constrained by the attack budget.

b) Eigen centrality: A related intuition of a node's importance is not just the number of neighbouring nodes to but the importance of the those nodes as well. A route that connects important drug routes is even more important. Accordingly, the eigen centrality of a node is algebraically computed as the sum of the centralities of neighbouring nodes, which are in turn connected to many others. The highest eigen centralities correspond to nodes located in dense partitions. Accordingly, the edge cutset comprises edges between the highest eigen-centrality nodes.

c) Betweenness centrality: The principal goal of the attacker is to deploy attack resources on edges that have the highest chance of usage. The Betweenness centrality of a node or an edge is the fraction of the shortest paths between all possible pairs of origin-destination pairs that include it. Since the defender wants to make deliveries within the constraints of distance and time, the shortest path between nodes of the tour would be a reasonable choice for the defender although not the most resilient choice. Accordingly, the attacker targets the set of edges with the highest Betweenness centrality in the graph. High centrality edges usually form a cutset separating dense subgraphs.

C. Modularity attacks

An alternate approach to mincut detection is offered by the notion of *modularity*. Modularity techniques uncover mincuts that partition a graph into two or more modules. The intuition behind modularity mincut detection is to search for graph components which have less edges than *expected* from an equivalent baseline. The baseline is a random graph [8] where the expected probability of an edge (i, j) is $d_i d_j / |E|$. Modularity of graph $G(V, E)$ is accordingly defined as:

$$Q = \sum_{i,j} A_{ij} - \frac{d_i d_j}{|E|}$$

where A is the corresponding adjacency matrix of graph G. To find the modularity mincut, a search algorithm (for modularity optimisation) is used to detect edgesets that can partition the graph into maximally modular subgraphs. A number of optimisation approaches have been proposed.

a) Greedy-modularity: Clauset, Newman, and Moore [6] propose a greedy algorithm to detect modularity mincuts. Starting from a set of disconnected nodes, the edges of the original graph are iteratively added in order to produce the largest possible increase of the modularity at each step. It has a complexity of $O(NLog^2N)$ on sparse topologies such as road networks.

b) Eigen-modularity: Newman [13] proposed a spectral optimisation approach to modularity maximisation. It combines the intuitions of eigen centrality (node centrality is recursively defined in terms of the centrality of its neighbours) with modularity (expected vs actual edge probability distributions) to isolate mincuts. This method works by calculating the most significant eigenvector of the modularity matrix defined as $B_{ij} = A_{ij} - d_i d_j / |E|$, where the first term is the adjacency matrix and the second term is the expected edge probability according to a randomised baseline. The graph is split into two partitions based on the sign of the corresponding element in the eigenvector, with the mincut being the set of edges across the two partitions. When there is no underlying structure to leverage, the eigenvector elements are of the same sign with the method returning a null cutset (as opposed to partitioning the graph into two partitions regardless of underlying structure).

c) Hierarchical-modularity: Blondel et. al [3] propose a hierarchical modularity optimisation technique for mincut detection. It starts with a set of isolated nodes, each within its own partition. Edges are added from the original graph in order to produce the maximum possible increase in modularity. In each iteration, edges and nodes may be reassigned for merging with a different partition with which it achieves the highest contribution to modularity. Each partition is replaced replaced by supernodes, yielding a smaller weighted network. The process is then iterated, until modularity (which is always computed with respect to the original graph) does not increase any further. This method offers a fair compromise between the accuracy of the estimate of the modularity maximum, which is better than that delivered by greedy techniques like the one by Clauset et. al [6], and computational complexity, which is essentially linear in the number of links of the graph.

D. Defense Strategies

1) Naive defenses: Our first defense strategy is the simplest of all, and is one that has been proposed by past work in network interdiction game [20], [15]. The defender navigates via a randomly chosen route to reach destinations on a tour. This is equivalent to the defender undertaking a Markovian random walk to complete deliveries on time. The intuition behind this defense is that by making random choices about the next part of the route the defender can hope to maximise the attacker's uncertainty about the defender's current location. Sanjab et. al [15] also provide a proof of the optimality of this defense.

The alternate obvious defense, is to enumerate all the disjoint paths between source-destination pairs and simply choose one of the routes uniformly at random. One might hope that there is enough redundancy within the network structure that multiple (disjoint) path routes exist and that the defender gets through most of the times and absorbs the delays on account of any attacks (being towed out of the attack zone).

Nice as these ideas may seem in theory, we find they do not work at all well in practice. In the Evaluation section, (Section IV) we examine the effectiveness of naive defenses against all the attack strategies and show that they are mostly ineffective when examined against real datasets.

2) Sophisticated defenses: Better results can be expected by designing defenses that are independent of attack strategies, inspired by a common heuristic for solving zero-sum games. The idea behind this approach is that the defender is indifferent to attack moves, resulting in a lower-bound of defence utility.

a) Inverse centrality defence: Accordingly, our first non-naive *inverse centrality* defense is a simple route-finding strategy that avoids edges that are commonly used as part of a shortest-path route between origin-destination pairs. And, where the attacker might hope to achieve a high rate of ambush. Specifically, the defender chooses routes to explicitly avoid high-centrality edges. The defender scores each edge i, j as a combination of Degree, Betweenness, and Eigen-centrality over node j. Degree centrality is easily computed as a local metric, and it is the most approximate form of a node's significance $C^D_{ij} = D_j / |E|$. Betweenness centrality is roughly the proportion of paths a node lies on $C^B_{ij} = \sum_{s \neq j \neq t} \rho_{st}(j) / \rho_{st}$, where ρ_{st} is the total number of paths between s and t while $\rho_{st}(j)$ is the number of st paths that include node j. And, eigen centrality further incorporates the notion of node significance as a function of being connected to significant nodes $C^E_{ij} = C^E_j = \frac{1}{\lambda} \sum_{v \in V} A_{jv} C^E_v$ where λ is the largest eigenvalue. A defender needs to balance between the various types of centrality hence they compute the harmonic mean over the three measures as follows:

$C_{ij} = \frac{C^D_{ij} C^B_{ij} C^E_{ij}}{C^D_{ij} + C^B_{ij} + C^E_{ij}}$

The defender then selects a route p that minimises the cumulative weight of the scores within the path i.e $D^p = \min_{e \in p} C_e$.

b) Mixnet routing defence: Our next defense is more sophisticated and derives from the theory of anonymous communications as developed in traffic analysis literature [7]. The defender assigns a random score (between 0 and 1) to each edge in the graph, and computes a route that minimises the cumulative weight of the route whilst completing the tour. This model was initially presented in Danezis' work on routing anonymously in sparse networks cited above, so we refer to it as Mixnet-shortest-path routing. In Danezis' model, each mix-router routes messages by forwarding them to a random neighbouring mix-router in order to maximise a global-passive adversary's uncertainty about a message's location within a mix network. This is strikingly similar to the defender's interest in resisting an attacker in our scenario. The Mixnet defense promises significant improvement over Markov chain routing proposed by previous work [15]. Mixnet routing not only randomises the defender's path but incorporates the notion of *latency awareness* by choosing the route that minimises the cumulative weight of (randomised) edge scores in the route. This increases the likelihood of the defender meeting delivery deadlines as compared to Markov chain routing. Since the random scores are only known to the defender, and each defender uses different edge scores, the attacker is unable to effectively predict the edge a defender may be traveling. As such Mixnet routing achieves a better balance between the maximal adversarial uncertainty of Markov chain approach vs the highly predictable shortest-path routing.

Variants of mixnet routing are possible that achieve a different tradeoff between adversary uncertainty and latency. For instance, a defender can follow (one of) the shortest path for most part but toss a coin at intermediate nodes and either continue to follow the shortest-path to the next hop, or undertake an $O(logn)$ random walk and regenerate a shortest-path route from the end of the Markov chain to the next destination on the tour. We will explore these variants in future work.

IV. Evaluation

We consider 12 different road networks corresponding to popular cities across the world where an automated real-time courier delivery system might be financially viable. The security game described in Section II is played in a number of rounds. Each round consists of an attack described in Sections III-A– III-C, when deployed against each of the defense strategies in Section III-D.

We simulate the interdiction game using real-world courier workflows. Our analysis proceeds as follows. We initially investigate the impact of each attack on the percentage of late deliveries when shortest-path routing or a defense routing strategy is employed in a multi-round game whilst also computing Nash equilibria. Nash equilibrium is the solution to our adversarial game, in which an attacker and defender choose a strategy while considering the opponents choice, and neither benefits by changing their strategy.

Initially, we focus on the cities of London and Beijing for which we have access to real courier traces. Subsequently, we validate our findings at scale using graph data from ten other cities.

Assumptions: We assume that the attacker has perfect information about the road network including traffic information as this information is publicly available. The defender also has access to this information, however the defender is not aware of the attacker's success rate on a particular route. This simulates the scenario that defenders belong to different administrative domains (i.e no single company owns them all) and hence their strategy selection is not coordinated. Our goal is to understand the lower bound for adversary success — the best-case scenario for operators of fleets of driverless vehicles. We assume that roads allow movement at the posted speed limits. Consequently, our analysis is the most optimistic scenario for developers of driverless vehicle technology, referred to as the defender.

A. London dataset

Our first dataset contains real courier traces for the city of London provided by eCourier (www.eCourier.co.uk). eCourier provides this data through the Open Street Map (OSM) project via a Creative Commons license. This dataset contains traces of actual courier movement over an eight week period in 2007 corresponding to half a million deliveries. Each delivery is associated with a delivery window which is a binary tuple composed of the earliest delivery time and the latest acceptable delivery time for the item. We also obtained the traffic and road maps for London via Open Street Map and generated a road network graph. Figure 2 shows the distribution of the delivery windows and we can observe that the average delivery window is about 2.2 hours. The average tour time in this dataset is $\sim$11 hours. We assume that each successful ambush causes a delay of $M = 10$ minutes. This is an optimistic estimate for the amount of time taken by a recovery vehicle to attend the scene of the attack and recover the vehicle to a new location, outside the attack zone. Longer delays would increase the delivery-failure rates experienced by couriers.

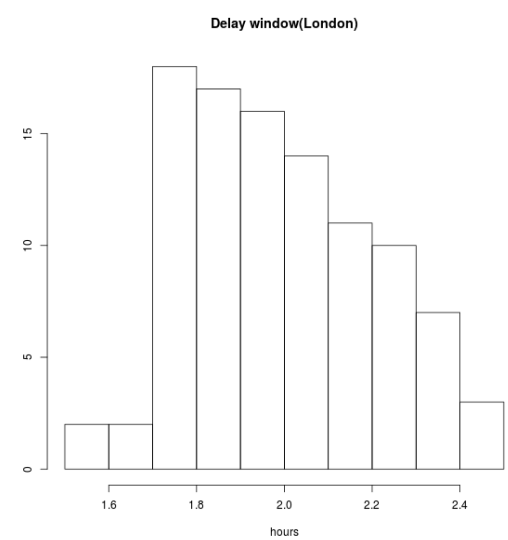


Fig. 2: Delivery Window (London)

Attacks vs. Defenses: We simulated the multi-round adversarial network interdiction game over 83330 delivery schedules within this dataset. Figure 3shows the impact on delivery time for every combination of nine attack strategies and three defense strategies, within a multi-round game involving thirty attackers (we justify this in a future section).

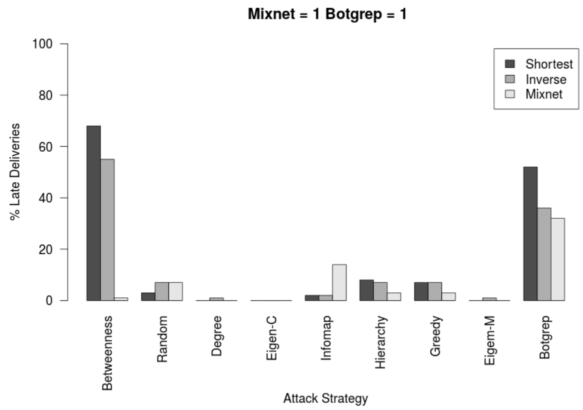


Fig. 3: Late Deliveries vs. Attacks (London)

Figure 3 shows that most attacks on driverless vehicles in London are effectively countered by shortest-path routing, with the exception of the Betweenness and Botgrep attacks. Betweenness attacks the edges which lie on the shortest-paths. Consequently, it caused 70% of deliveries to be late when the defender was using shortest-path routing. When the defender switched to Mixnet routing, there were no late deliveries, hence completely mitigating the attack. Mitigation is achieved by the randomness of Mixnet routing, which switches from using high-betweenness edges to leveraging edges that are a part of mid to low conductance cuts, in order to route efficiently. From Table I we can see that 65% of the late deliveries caused by the Betweenness attack were critically delayed (by >50% of delay window, eg 1.1 hours for London) when shortest-path routing is used. The Inverse defense strategy reduced the amount of critical delays by 10%, but Mixnet significantly reduced the critical delays to 1% of the overall late deliveries. When the attacker switches strategies from Betweenness to Botgrep, the Mixnet defense, unlike its effectiveness in defending against the Betweenness attack, was less effective compared to using shortest-path routing. The reason for this is that Botgrep (in common with other modularity-based techniques) attacks low conductance cuts which are crucial to Mixnet's routing efficiency, as they enable connectivity between sparsely connected localities. Interestingly, the Inverse centrality defense was the most successful at reducing the amount of late deliveries caused by the Botgrep attack. Overall, the amount of critical delays caused by Botgrep is less than Betweenness. Even though Mixnet is less effective against Botgrep compared to Betweenness, it still reduces the amount of critically late delays to 30% of the overall late deliveries, which is lower than if shortest-path routing or Inverse is used.

Next, we allowed attackers and defenders to adapt to eachother's strategies. For the city of London, we found a pure Nash equilibrium between *the Botgrep attack strategy and Mixnet defense strategy*. When adaptation is allowed, and the attacker employs the Betweenness attack, the defender can deploy Mixnet to suitably counter it. The attacker could counter the defender's move with the Botgrep attack, maximising the attacker's payoff against Mixnet. However, no other strategy increases the defender's payoff, and no other attack improves the attacker's payoff, hence constituting a Nash equilibrium.

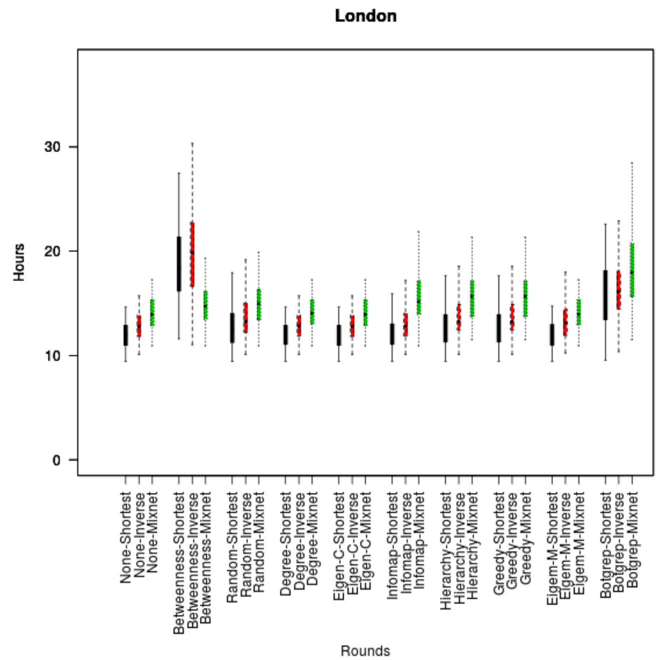


Fig. 4: Tour Time vs. Attacks (London)

Impact of attacks on tour time: We also measured the increased costs imposed by defences my measuring the numbers of hours a courier would need to work for. With no attacks, the average working day is ∼11 hours, shown by the length of an average tour when shortest-path routing is used (Figure 4). Even where defenses are successful in minimising the impact of attacks by ensuring the deliveries reach on time, the length of the workday increases significantly which constitutes the extra cost of resilience.

The Betweenness attack induces the largest increase in tour time compared to all other attacks on this dataset. Although the Inverse defense reduces the amount of late deliveries compared to shortest-path routing shown in Figure 3, it induces a higher tour length compared to shortest-path routing, with a worst-case tour time of around 24 hours. Interestingly, the average tour length when Mixnet is deployed against Betweenness is only slightly more than when Mixnet routing is deployed under no attack; we note however the the worst-case tour-length is significantly higher under attack.

We also observed that Botgrep does not induce as many late deliveries as the Betweenness attack, due to the overall tour time being relatively similar. Although Mixnet reduces the amount of late deliveries compared to Inverse and shortest-path routing for Botgrep, as shown in Figure 3, it incurs a longer tour time. Interestingly, the tour time incurred by Mixnet defense against Botgrep is similar to the tour time for the Betweenness attack with shortest-path routing, which caused the highest number of late deliveries in this dataset.

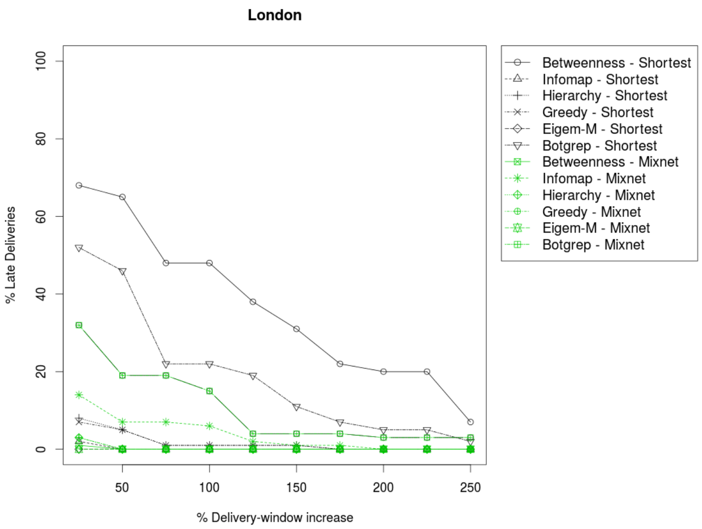


Fig. 5: Late Deliveries vs. Delay Window Increase (London)

Impact of delivery-window size: Next, we investigated whether increasing the delivery window — the buffer times available to a courier before a delivery is classed as late — would reduce the number of late deliveries. The average delivery window size within the dataset is 2.2 hours (Figure 2). The results of increasing the delivery-window size are show in Figure 5. Reductions in late deliveries start at around a 75% increase in the delivery window, which is 3.85 hours. Reducing the percentage of late deliveries to a serviceable level of 5% of total deliveries, requires significant increase in the delay-window size, which has implications for the numbers of hours a courier needs to work for to complete the day's work (or an increase in the number of couriers). For example, in order to reduce late deliveries from 75% to 10% for the Betweenness attack, this would require a delivery window increase of around 250% or around 5.5 hours per delivery.

Impact of attacker strength: To investigate the impact of the number of attackers units on late deliveries, we controlled for the number of attack resources available to the attacker. We assume these attack units are coordinated by a single attacker who coordinates the placement and strategies of all the attack units using a command-and-control network. As shown in Figure 6, as the number of attackers increases, increasing numbers of edges get attacked which result in increasing delivery times. We identified that on average, significant increases in late deliveries occur between 10 and 30 attackers. As well as this, attacks other than Betweenness and Botgrep show minimal or no increases in late deliveries, regardless of how many attackers are deployed. From these observations, we decided to run our previous experiments with a baseline of 30 attackers.

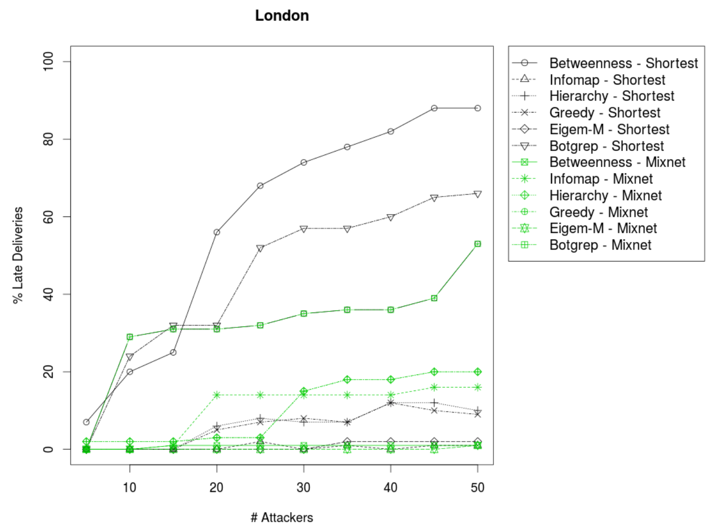


Fig. 6: Late Deliveries vs. # Attackers (London)

B. *Beijing dataset*

Our second dataset for the city of Beijing is two orders of magnitude larger than the London courier dataset. This dataset contains traces generated by 30000 couriers over a period of three months between making a combined total of 75 million deliveries. Figure 7 shows the distribution of the delivery windows and we can observe that the average delivery window is about 30 minutes. The average tour time in this dataset is $\sim$4 hours, owing to a large number of couriers being engaged for a fraction of a working day.

Attacks vs. Defenses: Figure 8 shows that most attacks had some degree of impact on the amount of late deliveries when shortest-path routing was used. Specifically, the Betweenness, Eigen-modularity and Botgrep attacks were successful in inducing high rates of late deliveries. The Betweenness attack is effectively mitigated by the Mixnet defense strategy, similar to London. Unlike London, the Inverse defense strategy incurs a higher percentage of late deliveries when employed against the Betweenness attack than if shortest-path routing is used. This is because London has higher redundancy in terms of the number of disjoint shortest paths within the road network. With an increased number of attackers running the betweenness attack, London can be expected to show a similar trend i.e Inverse performs worse than shortest-path routing. This does not mean there is not enough redundancy between origin-destination pairs in Beijing, however routing techniques based on shortest-paths cannot locate such routes. Mixnet routing however can do so. Similar to the London dataset, the Mixnet strategy also significantly reduces the amount of critical delays. This indicates the importance of leveraging low-

		Lon	Bei	Bris	Bham	Cam	Gla	Eburgh	Del	Chi	Bos
	Shortest	65	94	85	96	100	94	81	98	34	97
Betweenness	Inverse	55	99	88	98	100	88	82	97	40	72
	Mixnet	1	10	25	2	75	6	1	3	1	0
	Shortest	3	22	18	9	54	15	7	7	5	13
Random	Inverse	7	27	18	3	45	9	13	13	8	13
	Mixnet	7	24	16	6	51	15	13	12	8	9
	Shortest	0	4	25	0	15	31	11	2	0	0
Degree	Inverse	1	2	21	3	8	35	4	4	0	0
	Mixnet	0	1	54	0	3	13	4	1	0	0
	Shortest	0	3	32	0	17	2	1	0	0	0
Eigen-C	Inverse	0	2	42	0	12	5	0	10	0	0
	Mixnet	0	1	77	0	9	9	66	14	0	0
	Shortest	0	38	31	1	58	10	20	12	4	45
Infomap	Inverse	2	59	34	0	46	12	9	9	2	42
	Mixnet	14	4	30	7	50	52	11	40	2	6
	Shortest	5	86	76	11	95	35	26	85	13	4
Hierarchy	Inverse	7	77	69	23	94	31	23	83	14	5
	Mixnet	3	54	62	4	83	50	27	68	38	3
	Shortest	5	86	76	11	95	35	26	85	13	4
Greedy	Inverse	7	77	69	23	94	31	23	83	14	5
	Mixnet	3	54	62	4	83	50	27	68	38	4
	Shortest	0	72	2	3	82	0	32	39	2	0
Eigen-M	Inverse	1	74	3	5	81	2	27	30	5	2
	Mixnet	0	19	2	2	80	1	15	60	5	6
	Shortest	46	68	76	14	83	19	59	64	26	3
Botgrep	Inverse	36	74	77	15	82	27	48	57	18	5
	Mixnet	30	21	73	13	89	47	44	9	62	1

TABLE I: % of Critically Delayed Late Deliveries

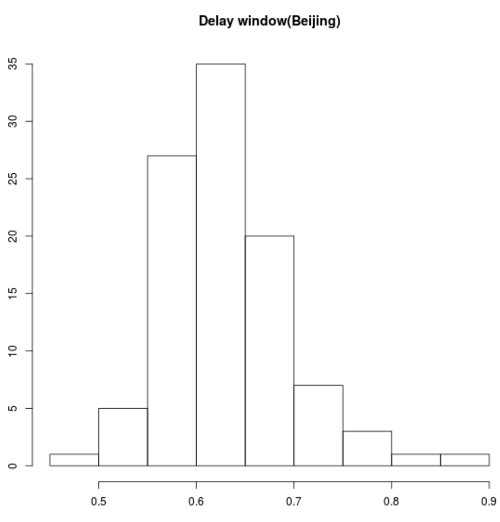


Fig. 7: Delivery Window (Beijing)

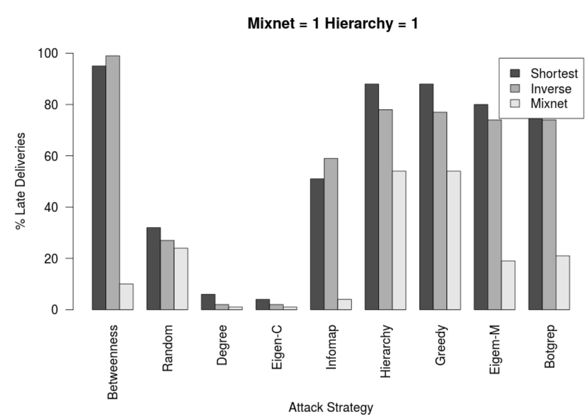


Fig. 8: Late Deliveries vs. Attacks (Beijing)

conductance paths rather than shortest-path routing to construct better defences.

In both London and Beijing, attacks leveraging betweenness centrality and low-conductance cuts are fairly successful, while Mixnet is the only serviceable defense. Table I, shows that the Betweenness attack causes 94% of late deliveries to be critically delayed and 99% of these delays to be critical when the Inverse defense is employed. Modularity-based attacks also induce high percentages of critically delayed late deliveries. High percentages of critical delays are induced by the majority of attacks with the exception of Degree and Eigen-Centrality, which is unlike the London dataset where high percentages of critically delayed late deliveries are only induced by the Betweenness and Botgrep attacks. Modularity attacks target low conductance cuts which Mixnet uses to improve routing efficiency. We expect to observe a higher amount of late deliveries when Mixnet is deployed against modularity-based attacks. This is demonstrated by the Hierarchy and Greedy attacks in Figure 8, with Mixnet incurring a lower percentage of late deliveries compared to the Inverse defense. In regards to conductance-based attacks, we find that Botgrep is a successful attack in London whereas Hierarchical-modularity is the most successful attack in Beijing.

As with London, we also found a pure Nash equilibrium in Beijing between the *Hierarchical-modularity* attack and *Mixnet* defense.

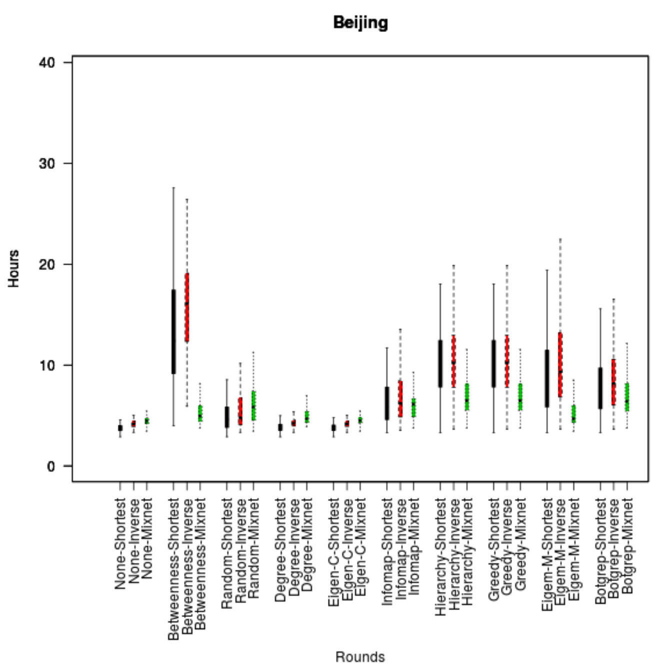


Fig. 9: Tour Time vs. Attacks (Beijing)

Impact of attacks on tour time: Next, we investigated the impact of the different attack strategies on the tour time of couriers. From Figure 9 we can observe that the average tour time for a working day is ∼4 hours, shown by the length of an average tour when shortest-path routing is used with no attack. Only a minimal increase in tour time is observed when defense strategies are employed with no attack strategy used. Similar to the London dataset, the Betweenness attack significantly increases the tour time of a courier to around 11 hours when no defensive-routing strategy is used. The Inverse defense further increases this, incurring a tour time of around 18 hours. Mixnet performs well to keep the tour time low, showing only a small increase compared to when it is employed against no attack strategy. From Figure 9, we can also identify that on average modularity-based attacks significantly increase the tour time compared to the average tour time by at least 50%. Mixnet however manages to reduce the tour time incurred by the modularity-based attacks by around the same amount.

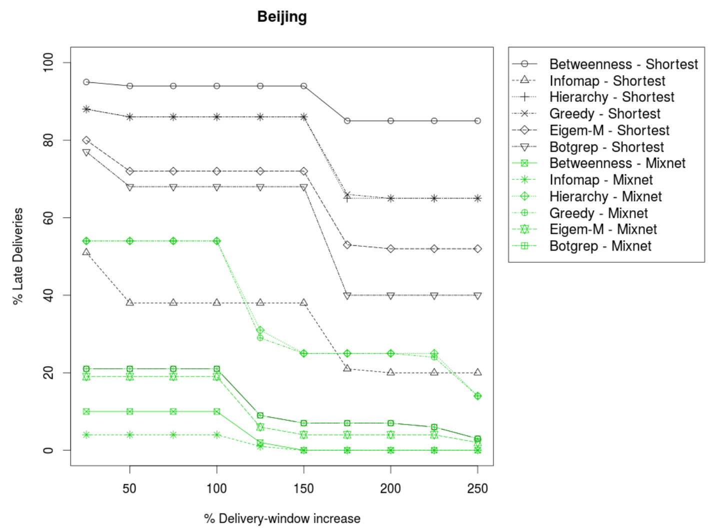


Fig. 10: Late Deliveries vs. Delay Window Increase (Beijing)

Impact of variable delivery windows: The next experiment we ran on this dataset was to investigate the impact of variable delivery windows on the amount of late deliveries. Figure 10 shows us that significant decreases in the amount of late deliveries only occur after at least a 100% in the existing delivery window. From Figure 7, we identified that the average delivery window was 30 minutes for this dataset. From our previous observation, we can deduce that a substantial reduction in late deliveries will be seen with a delivery window of about one hour. For an ideal amount of late deliveries, such as around 10% like the London dataset, an increase of at least 250% to the delay window (2.5 hours) is required. However, we can observe that attacks such as Betweenness still incur a very high percentage of late deliveries even with a 250% increase in the delivery window. This suggests that increasing the delivery window alone does not resolve the attack.

Impact of the number of attackers: Our final experiment on this dataset was to investigate the impact of the number of attackers on late deliveries. From Figure 11 we can see that on average, there are significant increases between 1 and 30 attackers. The baseline is derived by observing how many attackers are required to induce significant failure rates using any attack with shortest-path routing. We observe that Botgrep, Eigen-Modularity, Greedy modularity, and Betweenness are very successful even at a fairly low attacker count of 5–10 attackers. However, to keep our experiments consistent with the London dataset for comparison, we decided to use the same baseline of 30 attackers, as it covers the significant increases in late deliveries for attacks on averages.

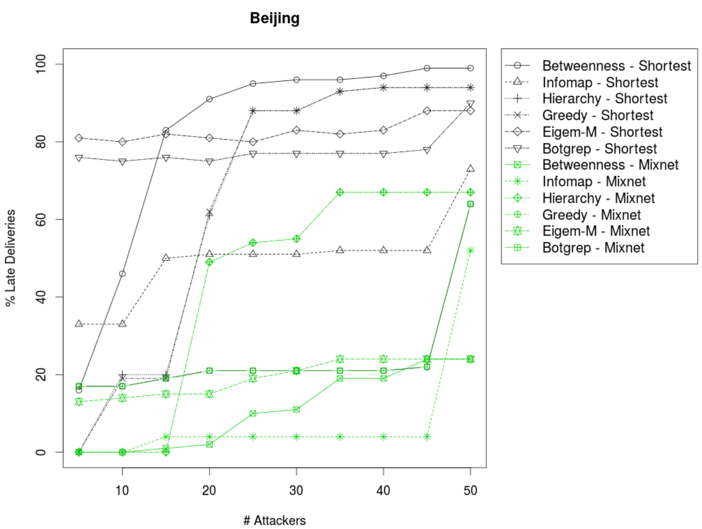


Fig. 11: Late Deliveries vs. # Attackers (Beijing)

C. Synthetic dataset

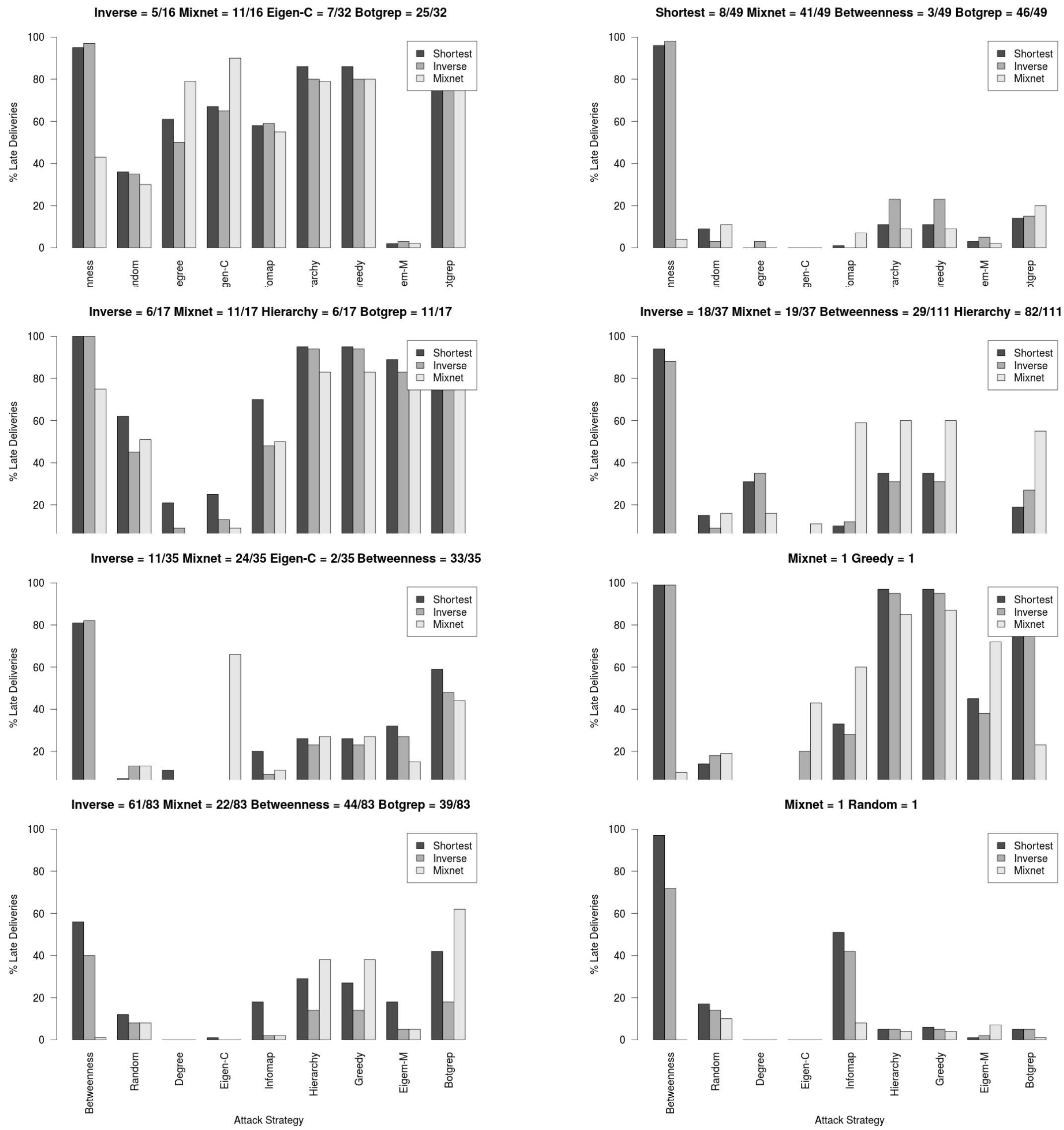
Our third dataset, is composed of synthetic courier traces combined with real road network data generated via OSM data for the following cities: Birmingham (UK), Boston (USA), Bristol (UK), Cambridge (UK), Chicago (USA), Delhi (India), Edinburgh (UK) and Glasgow (UK). The purpose of this dataset is to expand our analysis beyond London and Beijing. To generate synthetic traces, we use the London database as a basis. The number of couriers are maintained but the locations are randomised in a distance-preserving manner i.e the distance between consecutive locations is identical on both the synthetic and real job cards for any courier. In the London dataset, each courier has a job card created on a per-day basis, that lists the delivery locations, times, and a delivery window which serves as buffer to indicate the maximum possible lateness allowed. We replace the first location on the card with a location from the city of interest, chosen uniformly at random. The subsequent locations on the card are replaced with another random location such that the travel time between consecutive locations on the synthetic card is the same as real job card. The delivery window size (difference between the latest possible delivery time and the window start time) is also maintained the same as the London dataset. A job is marked late if it is delivered beyond the maximum allowable delivery period.

Impact of Attack and Defense Strategies: We first evaluated the effectiveness of the different attack strategies on the percentage of late deliveries for each of the cities in our synthetic dataset, as well as the effectiveness of these attacks when a defense strategy is employed, with the results shown in Figure 12. Overall, we observed that the Betweenness attack was the most successful attack on all the synthetic traces. For the Bristol, Birmingham and Edinburgh datasets, we noticed that the Inverse defense incurred a higher percentage of late deliveries compared to shortest-path routing, the same outcome shown in our results for Beijing. In our previous datasets, we observed that modularity-based attacks caused a large number of datasets but were mitigated by Mixnet. We noticed that for some cities in our synthetic dataset, such as Glasgow (Figure 12(d)), Mixnet performs exceedingly worse as low-conductance edges across dense clusters are identified and targeted by modularity-based attacks.

Similar to London, our results on the Birmingham dataset in Figure 12(b) show that the majority of attacks are not that effective. For example, the degree centrality attack has no impact on late deliveries even when no defense is employed. Interestingly, for most cities in our synthetic dataset, Eigen-Centrality attacks have little or no impact on late deliveries. More specifically, our results for Edinburgh in Figure 12(e) show that Eigen-Centrality with shortest-path routing incurs a very small number of late deliveries, but Mixnet causes $\sim$70% of late deliveries. To investigate this further, we looked at the number of critically delayed late deliveries for these cities shown in Table I. We identified that Mixnet causes 66% of the late deliveries for the Eigen-Centrality attack on Edinburgh to be critically delayed. Overall, we observed that for all cities in our synthetic dataset, with the exception of Chicago and Boston, the modularity-based attacks incur the highest amounts of critical delays. The results from the table do show that for all cities, Mixnet reduces the amount of critical delays — however, not substantially. This means that while Mixnet is able to mitigate the attack to some extent, these cities have relatively lower numbers of low-conductance cuts ($\rho < 0.076$) across localities which restricts the number of redundant paths available to Mixnet whilst under attack.

Effect of Attack Strategies on Tour Time: Our next experiment on the synthetic dataset was to investigate the impact on attack strategies on tour time. Figure 13 shows the effect of attacks on tour time. Overall, we observed that for most cities, the average tour time for a working day is between 8 and 10 hours. Boston has a slightly higher average tour time of $\sim$12 hours. The average tour time is shown by the length of an average tour when shortest-path routing is used with no attack. Interestingly, we identified that increases in tour time correlates with the percentage of late deliveries shown in Figure 12. For example, in Figure 12(e) our results show that Mixnet incurs a high amount of late deliveries when deployed against Eigen-Centrality. In Figure 13(e) we can see the same increase in tour time when Mixnet is used, with the tour time increasing from $\sim$10 hours to nearly 20 hours. The Betweenness attack also incurs the highest tour time for all cities, with Mixnet effectively reducing the tour time as well as the amount of late deliveries.

Impact of Delivery Window Size: Our final experiment on this dataset was to investigate the impact of the size of delivery windows on the amount of late deliveries. As previously



(g) Chicago, USA

(h) Boston, USA

Fig. 12: Effect on % of Late Deliveries for Attack Strategies

described, the synthetic dataset is based off the London dataset such that the delivery window size is maintained the same. Therefore we can state that for all cities in our synthetic dataset, the average delivery window is 2.2 hours. The results of this experiment are shown in Figure 14. For all cities we observed that the betweenness attack, regardless of the defense strategy, incurred the highest percentage of late deliveries even with an increase in the delivery window. For all cities, we noticed that substantial decreases in late deliveries only occur after in increase in delivery window of around 100% (4.4 hours). As well as this, Mixnet also substantially reduces the percentage of late deliveries in all cities and in some cases almost reducing the percentage of late deliveries to nearly 0% such as in Boston (Figure 14(h)). For most cities however, we would consider an ideal amount of late deliveries to be around 10% like with London and Beijing. From the results we can deduce that to achieve the ideal amount of late deliveries, we would require at least a 200% increase in the delivery window (6.6 hours). However for most cities, the Betweenness attack still incurs over 60% of late deliveries even with a 200% increase in the delivery window, suggesting that increasing the delivery window alone will not resolve this attack.

D. Discussion

Driverless vehicles are expected to be foundational components of future transport systems. Our results show that the topology of road networks plays an important role in the security of driverless vehicles. Thus it is important to consider network topology rather than solely focusing on the vehicles. We have shown that any physical-proximity attack on a driverless vehicle can be carried out at scale, if the attacker

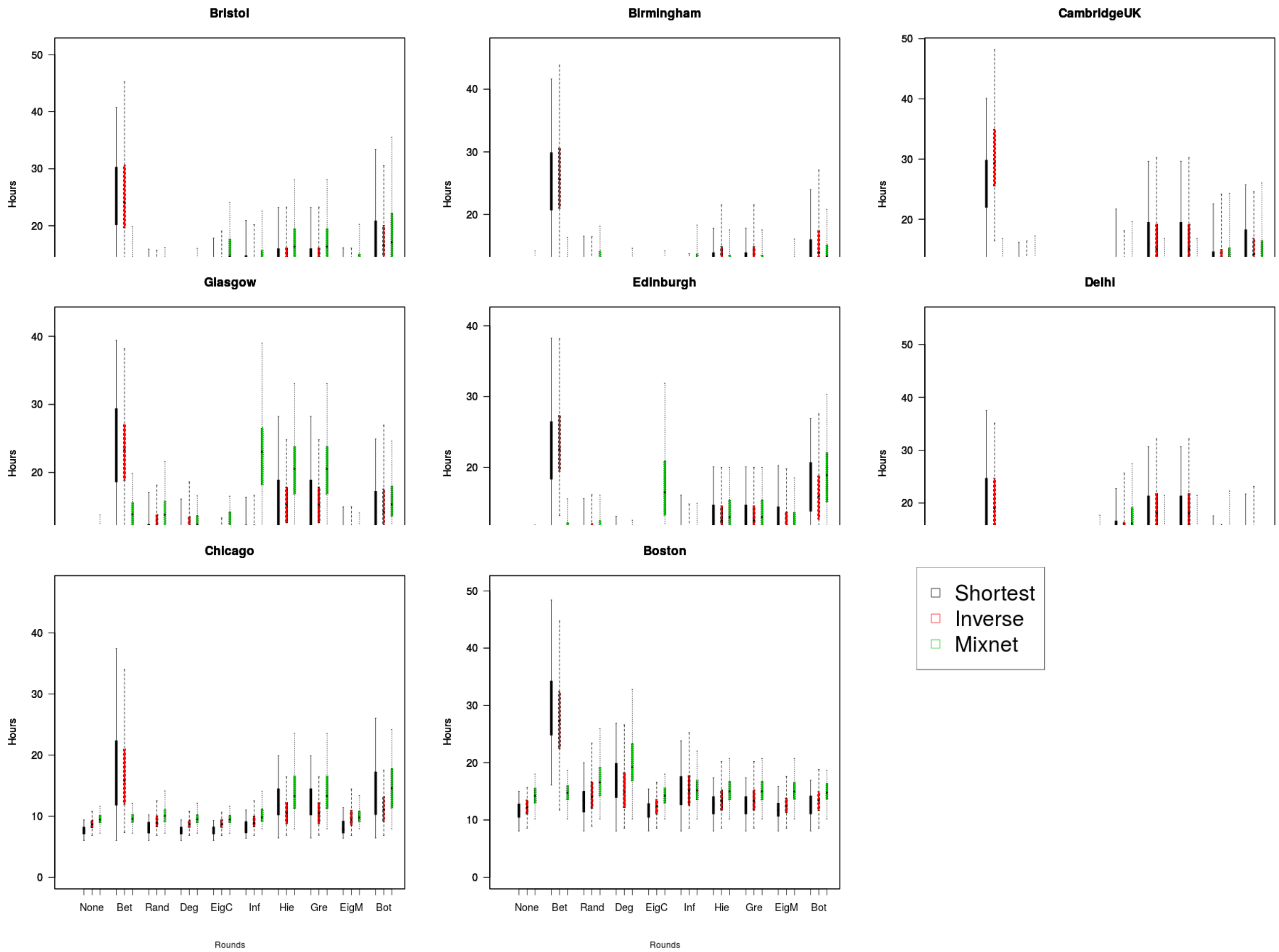


Fig. 13: Tour Time vs. Attacks

exploits certain "ideal" ambush locations. By exploiting these locations, attackers can transform host-level attacks into a practical attack that can target one or more fleets at the scale of an entire city. We found such locations in each of the twelve road networks we analysed.

We found that the mainstay of routing techniques used by driverless vehicles – shortest path routing (which solely focuses on efficiency) – is highly vulnerable to betweenness centrality attacks in all the cities we examined. As described in Section III-A, the betweenness centrality of an edge is the fraction of the shortest paths that include the edge. Thus the edges with highest betweenness centrality are ideal ambush sites against couriers using the shortest path routing strategy.

In contrast, mixnet routing performs significantly better than shortest path routing. Mixnet combines the notions of routing efficiency with randomness. Randomising a courier's route leads to greater uncertainty on the attackers part since the courier occasionally seeks alternatives to shortest paths to the next destination. In comparison with shortest path routing, mixnet routing reduces the number of edges with high betweenness centrality in the path, thus reducing the delivery-failure. In general, we found that delivery failure rate for mixnet was half the failure rate for shortest path routing, in most of the cities we evaluated.

In many cities, none of the defences produced serviceable results – even after deploying randomised defences – a coordinated attack by approximately 10–30 attackers, can cause between 20% to 50% of deliveries to be delayed, at a minimum, considering the application of Mixnet routing strategy. In cities like Beijing as few as 8 attackers are able to cause significant levels of disruption. An increase in the number of attackers reduces delivery rates approximately linearly as the number of attackers.

Switching the routing strategy from the default (shortest path) to a more resilient Mixnet helps, however further switching does not help in most cases. We found pure Nash equilibriums between attacks and defences in London (Mixnet vs Botgrep), Beijing (Mixnet vs Hierarchical modularity), and Boston (Mixnet vs Random). An equilibrium predicts the strategic behaviour of attackers and defenders, and specifically that switching from these strategy combinations is unlikely under the assumption of rationality.

For Bristol, Birmingham, Edinburgh, Delhi, Glasgow, Chicago, and Cambridge (UK), we found mixed-strategy equilibriums. This is due to a cyclical disruption in the dominance relationships between attack and defense strategy combinations. For instance, in the case of Edinburgh (UK), consider a courier who starts off using shortest path routing to minimise

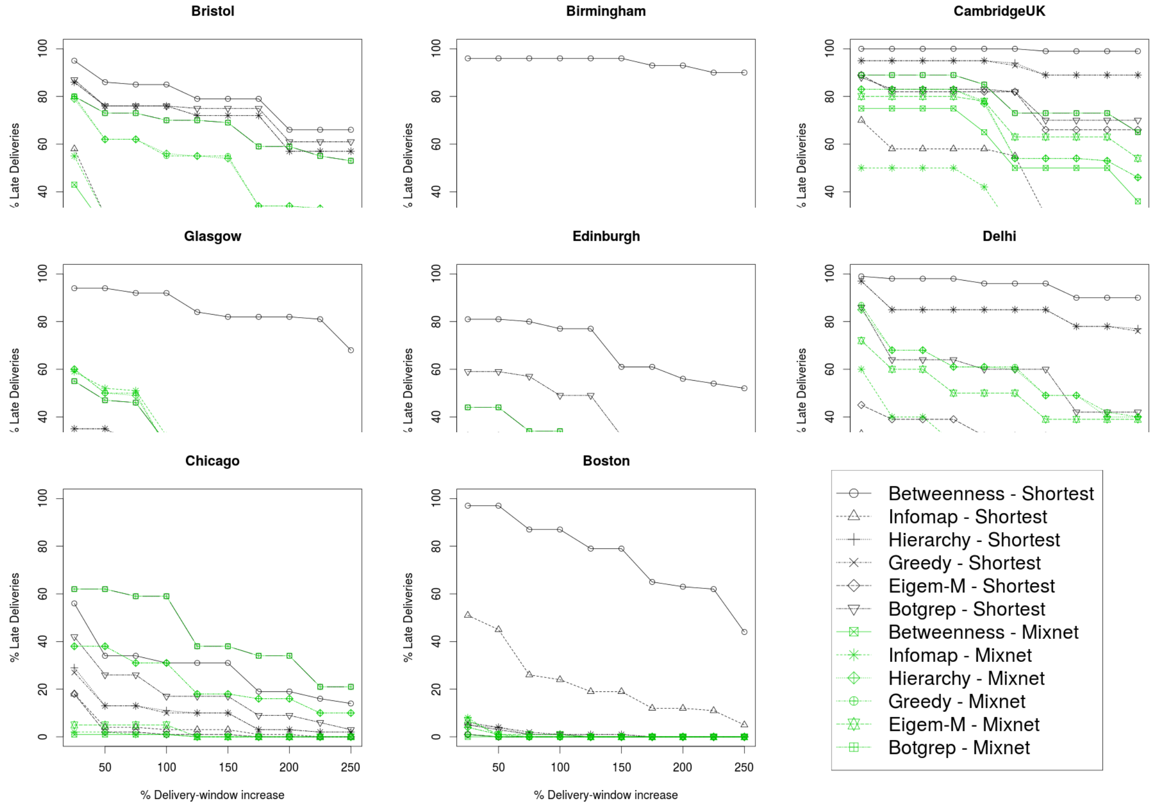


Fig. 14: Late deliveries vs Delivery Window Increase

their transportation time. The attacker exploits the couriers' use of high-betweenness edges and attacks them using betweenness centrality, which is successfully countered by the courier using mixnet routing which leverages high-conductance cuts instead of shortest paths to minimise transportation time hence being robust to betweenness attack. Subsequently, the attacker switches to Eigen centrality attack, which significantly increases the %late-deliveries under mixnet routing because of the high correlation between conductance-cut edges (used by mixnet) and high eigen-centrality edges. As a response, the courier can switch to leveraging the shortest path routing or inverse centrality defense, to shift from using high-conductance edges. The attacker naturally switches to betweenness centrality, thus completing a cycle – (Betweenness, Mixnet, Eigen-C, Inverse, Betweenness, . . .), which iterates. The cycle is stable since the dynamics of attack and defense constitutes a nash equilibrium.

We observe from the late delivery rates in figures 12, 8, and 3, that in all cases, the effectiveness of inverse centrality defense is not very different from that of the shortest path routing, against the betweenness centrality attack. To be clear inverse centrality is not the inverse of betweenness centrality. It is the harmonic mean of three edge centralities including betweenness. However, since road networks show low diversity in degree centrality, the resulting edge choice for a route is a function of betweenness (i.e shortest path) and eigen centrality (edge importance as a function of other edges). Here betweenness plays the major role as evidenced by the similar damage sustained by couriers using either shortest-path routing or inverse-centrality routing whilst under a betweenness centrality attack.

Many of the Nash equilibriums we observed for the various cities we analysed are contain combinations of attacks and defenses that occur together frequently. See figures 12, 8, and 3. For instance, a combination of Botgrep and Betweenness attacks are found in an equilibrium with a combination of defense strategies of shortest path and mixnet routing. To understand why this occurs, we need to consider why some attacks are good at covering a broad spectrum of the attack surface. Efficient routing in so far as the strategies considered in this paper are based on two intuitions: shortest paths and high-conductance paths. Couriers using shortest path routing strategy are ambushed with high probability by attackers deployed at high-betweenness locations, and counter it by switching to mixnet routing that leverages a combination of min cuts, path randomisation, and shortest paths. However, the attacker can in turn counter that defense using botgrep which is specifically designed to uncover high-conductance cuts using a two-stage random walk method. This forces the courier to revert to the shortest-path routing, and the cycle continues.

While some defences can be effective against some attacks many challenges remain. Our work demonstrates that the well known shortest-path routing strategy will fail miserably, with delayed deliveries approaching 80–100% in most cities we analysed, with the exception of Chicago, which has a lattice road-structure that offers slightly better resilience (60% late deliveries). This reduction arises from the fact that outside of high betweenness centrality roads, the edges of the lattice provide a large number of alternate paths between origin-destination pairs with little diversity in their importance.

E. Tactical aspects

Previous work has shown that host-level attacks can be mounted via sensor saturation [21], [18], [16] or by exploiting the impact of adversarial inputs on machine-learning techniques [9], [17], [10], [19], [4]. Up until now, no techniques have been proposed as to how attacks on individual hosts can be scaled. However, network effects of the road systems might start to change that as attackers realise they only need to be located at a fraction of possible locations to consistently ambush their targets.

While the strategic aspects favour the attacker, do the tactical options exist to complement it? This question can be answered by considering whether the cost of using jamming equipment, amongst others, in a deployed attack unit is economically viable when deployed to disrupt a fleet of courier vehicles. From our results, we know that an adversary only requires 25–30 mobile attack units, in order to “cover” an entire city. Commercial GPS jamming equipment retails for around £2000 and a laser gun mounted on a high-precision industrial robot arm such as a UR3 device retails for around £9000, with cheaper alternatives available in the market. This constitutes a burden of approximately £9000 per attack unit excluding the mounting platform, adding up to a total budget of roughly £250,000. The costs of moving the equipment can be minimised by slightly increasing the total budget to statically occupy ambush points defined by either high-betweenness or high-conductance edges. In terms of the damage inflicted, the losses accruing from failed promises to deliver on time has some link to repurchase intentions. According to [5], the inability to deliver on time just once can result in a reduction of 14% of current purchasers submitting a future order. An inability to deliver on time twice reduces the customer base by a cumulative total of 26%. Conservatively, assuming this results in the loss of an order of magnitude lower loss in revenues from one city, it would mean an indicative loss of 2-3% of revenue per city. Depending on the volume of trade (given that some retailers filed tax returns of global revenues of three figure billions of dollars) potential losses could run into millions of pounds in the top-1000 large cities where most of the business is done. We note however that these are very rough calculations to examine the viability of tactical options and should be considered no more than a sanity check. It is also worth noting that the impact of late deliveries on customer satisfaction and future trade depends on cultural and personal attributes, therefore generalising on the basis of a scholarly study focused on any small part of the world is not advisable.

V. Related Work

The game-theoretic background to the problem at hand lies in the search game within predator-prey games, also known as hider-seeker games. This is a zero sum game between a single predator and a single mobile prey. The predator and prey move about in a search region. The game ends with positive payoff to the predator when it meets the prey. As a bio-inspired example, the *blancardella* wasp finds larvae by searching for visible evidence of leaf-mining. Wasps are attracted by the appearance of holes or other leaf deformation created bythe leaf-mining larvae. The game begins when the wasp lands on the leaf to search for the larvae, who in turn is alerted by the vibrations caused by the landing wasp triggering evasive behaviour by larvae. When the wasp encounters a feeding hole, it repeatedly inserts its ovipositor violently in the area to ambush the prey. The game ends either with the wasp paralysing the larvae or abandoning the leaf. The formalisation of this problem is well studied within pursuit-evasion games [1].

A particular form of hider-seeker game called an interdiction game [20] which was originally developed to understand and intercept drug smuggling in the 90s. In an interdiction game, one or more smugglers (hiders) attempt to traverse a path between two nodes on a network while the police (seeker) patrol certain routes intensively to interdict smugglers. Both the players are intelligent and adapt to eachother to avoid being predictable. Our work uses Wood’s game formulation as the starting point.

Work on security games and robotic patrolling has focused on concrete applications of *path-disruption* games [2]. Here the hider attempts to reach a well known target whereas the seeker wishes to prevent that. The dynamics of attack and defence strategies is well understood in the static target problem — a static target is appropriately ring fenced by the defender via a defence-in-depth approach. In our multi-party network interdiction game, the targets are multiple as well as being dynamic as courier deliveries involve dropoffs at numerous locations.

VI. Conclusion

There is significant interest in using autonomous or driverless vehicles to achieve cost reductions in transport logistics of parcel deliveries and taxis to enable point-to-point transport. A major barrier to this vision is a holistic understanding of the systemic challenges across connectivity, mobility, and security. In addition to carrying out reliable data acquisition through redundant sensors, securing vehicular communications, and the host (vehicle) itself, we need carefully designed redundancy within vehicle routing infrastructure. And, routing techniques that can leverage them via adversarially-resilient routing algorithms. As a first step in this direction, we have carried out the first systematic analysis of the attack and defense strategy space. We showed that launching targeted attacks in an optimal fashion is an NP-hard problem. We then applied approximation algorithms to study the dynamics of attack-defense efficiency by constructing the adversarial TSP game. We found that most of these attacks were very effective against the shortest-path routing technique which is a commonly used routing technique, while Mixnet routing was the best defense strategy. Our analysis of the adversarial TSP game identified several Nash Equilibria which offers a predictive view of which attack and defense strategies are important. While the study is not perfect in that we haven’t considered the effects of congestion, we offer a lower bound of adversarial success as congestion will further reduce the fraction of on-time deliveries. There are several avenues for future work. First, our analysis would be improved by considering the effects of congestion. Second, our analysis may be improved by considering temporal aspects (observing how variance on the traffic graphs impacts our results). Finally, we do not attempt to address the challenging problem of providing countermeasures i.e how to build redundancy into the road network and designing defensive-routing schemes that can leverage that redundancy when needed.

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