Cascading Failure From Targeted Road Network Disruptions

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Recent natural disasters have shown that urban road networks are susceptible to cascading failures as evidenced by city scale traffic jams. Further, the rise of internet connected vehicles and smart city infrastructure leads to the potential for hackers and nation states to target disruptions that maximize the potential for cascading failure. While cascading failure in networks have been studied extensively, the spatiotemporal nature of how cascades spread is lacking. Here, we quantify the potential for targeted disruptions on urban traffic networks. Guided by microscopic traffic simulations, we develop a theoretical framework for predicting the growth in cascading traffic jams around road disruptions. We apply our framework to the city of Boston using previously validated origin-destination pairs from cell phone location records. Application of our framework to Boston reveals that a targeted disruption of roads leads to disproportionately large proportion of shortest time routes being blocked, due to the relative importance of a few key roads. We find that an initial targeted disruption quickly impacts a significant portion of incoming traffic. Depending on the percentage of initial disruption, vehicle density, and characteristic free flow trip time the cascade occurs on the minutes to hours timescale. However, connected component analysis reveals that route redundancy provides an order of magnitude improvement in fragility, demonstrating the potential for strengthening transportation against network failure.

INTRODUCTION

Societal responses to epidemic and hurricane disasters have highlighted that we are a reactive, rather than proactive society. This lack of proactive response combined with the interconnected network nature of critical societal functions leads to cascading failure, often witnessed in urban road networks. Because of the complex nature of urban traffic, there is a lack of comprehensive understanding of how localized disruptions propagate to city scale traffic congestion.

There have been fundamental advances over the last century in understanding how interactions between individual drivers lead to the emergence of traffic flow patterns, including kinematic wave models [1] and microscopic traffic simulations [2-5] that reproduce general features of traffic flow. However, understanding city-scale traffic patterns are more difficult due to the dynamic nature of urban traffic. To this end, a number of traffic simulation platforms have been developed [4,5], that use validated models of vehicle interactions in traffic, combined with dynamic assignment [6] of origin-destination pairs and routing for vehicles on road networks. With the recent availability of granular trip information through GPS data and cell phone records [7,8], there have been advances in reproducing and simulating existing traffic patterns [9-11], still limited by the sparse nature of this type of data.

On the other hand, recent studies have shown that city scale traffic congestion follow reproducible patterns that can be understood through percolation theory [11,12], or simple contagion like spreading models [13]. While understanding daily city traffic patterns is difficult, it remains a considerable challenge to develop a predictive model of traffic dynamics around network disruptions such as during disasters, evidenced quite often. For example, the costliest storm in history, Hurricane Irma in 2017, was accompanied by 100 mile cascading traffic jams.

Apart from natural disasters, the coupling of vehicles with the internet leads to the potential for novel disruption hitherto unquantified. It is estimated that 20% of vehicles in the US can connect to the internet, and this market share is growing every year. Along with the growth in connected vehicle surface area, comes the risk of vehicular hacking. There has been a growth in incidents where hackers have demonstrated that they can gain control of critical vehicle functions such as brake, engine, and steering [14-16]. Various surfaces have been found for example through vehicle entertainment control unit [16], spoofing vehicle sensors like LIDAR [17], and poorly authenticated 3rd party apps that are linked to critical vehicle safety functions [18]. Ultimately, it becomes very hard to ensure that vehicles are completely secure against vulnerabilities. One of the greatest security threats for connected vehicles are fleet wide hacks, stated by Tesla CEO Elon Musk in 2017 [19]. Thus a significant concern is hackers targeting roads for maximizing cascading disruptions.

While cascading failure [20,21] is a well known problem across multiple critical infrastructures [22] including the power grid and transportation systems such as cascading traffic jams during evacuations [23] and aircraft delays [24], the spatiotemporal nature of cascading failures is not yet well understood [25]. In a recent study [26], it was found that a 5% random disruption of roads would entail an average additional annual delay of 30%.

Here, we develop a framework for quantifying the cas-
FIG. 1. Snapshots from SUMO traffic simulations on a 5x5 grid. (a) Low density traffic, 30s after hack. (b) Traffic 200s post-hack. (c) Traffic after 400s cascading to adjacent roads.

cascading fragility to targeted disruptions through a combination of microscopic traffic simulations on grid networks, theoretical modeling, and city origin-destination (OD) data. From the application of our framework to shortest time routing on Boston, we find a small percent of targeted nodes (1%) leads to a disproportionately large fraction of vehicle routes impacted (40%), which is compounded by vehicles forming traffic jams on adjacent roads. We find this initial disruption quickly cascades to the city scale in minutes to hours depending on the vehicle density (rush hour vs non-rush hours), and number of roads disrupted initially.

While shortest time path disruption is a significant risk due to a large fraction of vehicles impacted, this does not necessarily mean that destinations are inaccessible. In order to understand how targeted route removal impacts connectivity, we draw inspiration from percolation theory. Percolation theory has been applied to traffic networks to infer the emergence or disappearance of connected components and understand the fundamental properties of road traffic networks and flows [12, 27, 28]. Our connected component analysis shows that while shortest time routes are significantly impacted, major-
FIG. 2. Cascading traffic jams around disrupted roads on 5x5 grids. (a) Initial disruption of a single road between 2 nodes (red). (b) Disruption cascade to neighboring roads through traffic jams of stopped vehicles. (c) Probability kernel $P(N_S)$ showing the probability that vehicles routes are blocked with number of stopped vehicles. Initially, $\sim 6\%$ of routes are blocked due to a single road disrupted and $\sim 90\%$ of routes are blocked when half the roads are disrupted. Dashed lines are theoretical prediction.

FIG. 3. Cascading traffic jams around disrupted roads on grids. (a) Growth of stopped vehicle traffic jam with time, colors correspond to different numbers of initially blocked roads along with theoretical formula (black lines). (b) Theoretical vs experimental time at which number of vehicles in the blockage is half of grid capacity corresponding to different sizes. Dashed black line denotes equality between simulation and theoretical prediction.

$$P(N_S) = 1 - \left(1 - \frac{N_R}{N_T}\right)^{\min(h_0 + N_S/25, N_T)}$$

Here, $N_R$ denotes the average number of edges in a route (which is 5 for 5x5 networks), $N_T$ is the total number of edges in the network (80 bidirectional roads in a 5x5 network and 360 in a 10x10 network), $h_0$ is the initial number of disrupted roads, and $N_S$ is the number of vehicles in the blockage. Since there are a maximum of 25 vehicles possible in each 200m edge (8m separation between vehicles), $N_S/25$ represents the number of additional roads blocked from cascading vehicle blockages. However, this is limited by the maximum number of edges that can be blocked ($N_T$), given the finite size of grids.

Using this probability, we developed a theoretical formula to predict how the number of stopped vehicles grows.
in time, as a function of $P(N_S)$, rate at which vehicles enter the simulation $r$, and the maximum capacity of vehicles in the grid, $K$:

$$\frac{dN_S}{dt} = r \cdot P(N_S) \cdot \left(1 - \left(\frac{N_S}{K}\right)^2\right)$$

(2)

In equilibrium, $r$ is related to the time spent by vehicles and number of vehicles in the simulation at any given moment as $r \cdot T = N$. Further, $T = N_R \cdot 200/v$, where $v$ is the average velocity of vehicles in the simulation in m/s and each road is 200m long. $r \cdot P(N_S)$ denotes the contribution of vehicles entering the simulation to the rate of growth of vehicle blockage. In the limit no routes are blocked, $P(N_S)$ is 0, and there is no growing blockage. When all routes are blocked, $P(N_S) = 1$ and all vehicle routes are blocked, thus all incoming vehicles enter the blockage.

The $(1 - N_S/K)$ contribution is due to the finite vehicle capacity of the grid. As more of the grid is occupied by traffic jams, vehicles cannot enter the simulation at their intended origin, which diminishes the rate of growth of stopped vehicle blockage close to grid carrying capacity. The $(1 + N_S/K)$ term is because existing vehicles in the simulation cannot reach their intended destination due to the growing traffic jam, and instead attach to the growing vehicle blockage quicker than their intended destination. Thus, the $(1 - N_S/K)^2$ term accounts for vehicles not able to leave depart from their origin due to growing vehicle blockage, as well existing vehicles that attach to the blockage on their routes. Figure 3a shows that the theory matches traffic simulation results quite well for different initial numbers of roads blocked, as well as for simulations of different grid sizes (Fig. 3b).

In our SUMO simulations on a grid, routes were chosen randomly, and each road has the same importance as every other route. However, in city road transportation networks certain routes like central highway systems are more important than others. Our theoretical $P(N_S)$ would not hold in real traffic due to not all roads being equally important in routes, as well as correlations between roads in routes.

In order to understand the fragility of urban routes to targeted disruptions, we apply our framework, in particular the probability kernel $P(N_S)$, to real trips in Boston. For Boston route information, we use data from a previous study which obtained OD pairs from travelers during peak 7-8 AM rush hour [8]. The OD information was obtained through tracking of cell phone records of a target population during that period. To analyze Boston road networks, we used OSMnx [30], a python package for working with Open Street Maps. The resultant map of Boston contained information about nodes and edges. Nodes correspond to intersections and edges to roads that connect intersections. While we do not have granular information about the routes taken, we obtained the shortest time paths corresponding to the OD data in the Boston road networks. For each route, we obtained all the nodes in sequence, corresponding to the shortest time path.

In nominal traffic conditions, one would expect the various map applications to show the shortest time paths. Figure 4a shows the top 5% of nodes (red) in the Boston road network. Visually, it appears most of the nodes are clustered around highways like I-90 and central streets such as Washington street. When these roads are initially disrupted, this cascades to adjacent roads as can be seen in Figs. 4b,c.

Surprisingly, we find that most of the shortest time
routes from the OD pair data pass through a very small fraction of nodes. Figure 5a shows that 10% of all shortest time routes pass through the single most important node, and almost 75% of routes pass through the top 5% nodes in Boston. This shows that the Boston routing network is extremely fragile to a targeted disruption of a few essential nodes. Once vehicles start piling up, the situation cascades to city scale failure. In the case of the single most important node being shutdown, a traffic jam involving 10% of the Boston vehicle capacity would result in 30% of shortest time routes being blocked.

We apply our extracted kernel $P(N_S)$ to reveal the dynamic cascade in Fig. 5b. For this, we obtain the maximum number of vehicles possible in Boston ($K_{Bos}$) by dividing the total road length* number of lanes in m/8; assuming a uniform spacing of 8 m between vehicles at maximum capacity which corresponds to a maximum density $\rho_{max} = 125$ vehicles/km/lane. We also obtain the typical time for routes using the shortest time path information during free flow, and set the rate at which vehicles enter as $r(\rho) = N(\rho)/T(\rho)$, corresponding to various densities. In order to find $T(\rho)$, we use: $T(\rho) = T(\rho_0)/(1 - \rho/\rho_{max})$, which is an interpolation from maximum velocity during free flow to 0 velocity at maximum capacity ($\rho_{max} = 125$ vehicles/km/lane). From OSMnx, we find the average of all shortest time routes within Boston, and multiply by a calibration factor of 1.3\cite{8}, from which we get $T(\rho_0) = 7$ minutes. This average time is for trips that have both origin and destinations within the city of Boston. However, this neglects trips that either originate from the city of Boston have a destination outside the city or those that originate outside the city of Boston and whose destination is within the city. If fact, we observe from the OD data that only 30% of trips with either origin or destination within Boston have both origin and destination within Boston. Thus, travel time by only considering vehicle routes with both origin and destination within the city could highly underestimate the average time spent by vehicles in the city. In order to have an upper bound estimate, we select the longest trip multiplied by the above calibration factor of 1.3, which is 35 minutes. From this analysis, we obtain a lower and upper bound of trip time and thus a bound in cascading disruption time. We apply these values in the formula below:

$$\frac{dN_S}{dt} = \frac{\rho K (1 - \rho/\rho_{max})}{T(\rho_0)} \cdot P(N_S) \cdot \left(1 - \left(\frac{N_S}{K}\right)^2\right)$$

This formula shows that disruption time depends on the percentage of nodes disrupted initially, density, and average free flow time. Figure 5b shows that at low density of $\rho = 6$ vehicles/km/lane, (blue circles in inset), time at which half of Boston is filled varies from less than 100 minutes to 170 minutes, depending on the percentage of nodes initially disrupted. Interestingly, above 5% of nodes hacked, there is a point of diminishing return.
above which more nodes disrupted does not speed up the ensuing cascade.

A similar trend is also observed at larger density of $\rho = 60$ vehicles/km/lane - above 5% of nodes disrupted there is a plateauing of disruption time. However, a stark difference from the disruption at low density is how quick the cascade occur. In this scenario, the resulting cascade is between half an hour to a few minutes, and is especially of concern. Using $T(\rho_0) = 35$ minutes, we find larger disruption time, 500-800 minutes at low density and 100-180 minutes at high density. This is because for the same density, longer trips imply lower rate at which vehicles enter. One caveat though is that this theoretical analysis does not take rerouting and recovery into account.

While shortest time paths are the most convenient, road networks also have redundancy. To understand the impact of redundancy, we did a connected component analysis inspired by percolation theory, to understand when routes are completely disconnected, thereby making them inaccessible. In order to minimize computation time, we randomly sampled 1000 routes and observed how many of them remain accessible at different levels of random and targeted node removals.

We found (Fig. 5c) that only 10% of top nodes removed leads to half of the routes being inaccessible. The spread in curves is due to the error from random sampling. For random disruption, we found that 15% of random nodes removed would lead to half of the routes being inaccessible. Thus, while a targeted disruption of 1% of roads leads to nearly half of routes immediately disrupted, the built in resiliency of the road network ensures accessibility of majority destinations, unless more than 10% of roads are targeted.

**DISCUSSION**

We have developed a framework for quantifying cascading impacts arising from targeted road disruptions. Our results show that while optimal city routes are particularly fragile to targeted disruptions, city road networks offer a buffer due to inherent road network redundancy. First, we develop a theoretical framework to predict the growth of large-scale traffic jams containing stopped vehicles on model grids. We then apply our framework to the city of Boston and find that nearly half of shortest time routes between OD pairs are immediately disrupted when only 1% of top nodes are shutdown. The ensuing cascade of vehicles blockages takes minutes to hours depending on the overall vehicle density and extent of disruption. However, these OD pairs are still connected through sub optimal paths until a disruption of more than 10%.

In a recent study [27], we found that a large-scale hack involving 20% of vehicles during rush hour would leave more than half the city of Manhattan fragmented and inaccessible from the rest. This was a static estimate, essentially due to hacked vehicles blocking roads and making them physically inaccessible. Here, we see two different failures. Dynamic routing failure occurs at 1%, whereas road network failure occurs at 10% of nodes disrupted.

One thing to keep in mind is our theoretical predictions assume a uniform distribution of vehicles entire throughout the road network. An interesting question is how heterogeneities in traffic density impact the resulting cascade. This cascade could be further amplified by existing traffic jams prior to the cascade. While we have assumed uniform flows and densities, traffic is a non equilibrium problem and jams are observed frequently in the absence of obvious disruption.

Our results highlight the impacts of lack of coordinated routing during disasters when roads fail or are intentionally disrupted. Of particular concern is that a very small fraction of roads targeted impacts most of the incoming routes. In this scenario, it is possible that vehicles that are not alerted and routed quickly become part of city scale traffic jams of stopped vehicles. This would lead to road network failure, where destinations are inaccessible, and is of particular concern especially for emergency vehicle. However, in the event that vehicles are alerted immediately and coordinated to not pass through the disrupted roads, the disruptions would be limited to initially impacted roads, and not cascade to city scale network failure. Drawn together, our results offer new possibilities for coordinated network level response to road disruption that minimize cascading impacts and prioritize evacuations.

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