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SIMULATING DDOS ATTACKS ON THE US FIBER-OPTICS INTERNET INFRASTRUCTURE

Sumeet Kumar
Kathleen M. Carley

School of Computer Science
Carnegie Mellon University
5000 Forbes Ave
Pittsburgh, PA 15213, USA

ABSTRACT

Network-based attacks like the distributed denial-of-service (DDoS) attacks are not new, but we are beginning to see attacks of unprecedented scale. Examples of such attacks include the 2016 attack on DYN INC that crippled a part of the Internet for hours, and the attack on Liberia, which partially brought down the African nation. Limitations in identifying vulnerable Internet infrastructure and testing possible defense strategies are a part of the problem. We need a simulation testbed that can reflect the complexity of the Internet, yet allows to swiftly test attacks, providing insights that can apply to real-world attack scenarios. In this research, we have designed a test-bed that mirrors the Internet infrastructure of the US and can simulate the Internet traffic flow patterns for different attack targets. We also estimate the degradation in the quality-of-service and the number of users impacted in two attack scenarios.

1 INTRODUCTION

Network based cyber-attacks like DDoS appear to be a growing phenomenon (Inofsecurity 2016). However, there is no clear understanding of where the attacks are coming from, how the attacks are organized, and how the attack targets are identified. While it is known that a majority of these attacks are originating from bots (Kandula et al. 2005, Alomari et al. 2012), there is lesser clarity on where the bots are located (Kumar and Carley 2016b) and how the bots are controlled (Stinson and Mitchell 2007, Santanna et al. 2015). To add to the puzzle, the specific impact and maximum possible damage of such attacks are also not known, and we only estimate the impact after the attacks have happened. However, one thing is clear that the bandwidth used in these attacks are increasing with time (Inofsecurity 2016). In a recent example of the cyber-attack on the African nation of Liberia (Kumar 2016), thousands of bots targeted the fiber-optic cable exchange point (IXP), bringing down the Internet connectivity of the entire country for almost a day. Another example is the attack on Estonia (Ottis 2008), which crippled the Estonia's government web-services for a few weeks. These incidents highlight the serious nature of such attacks and call for policies to counter them (Kumar, Benigni, and Carley 2016), and ways to understand and control them (Yu et al. 2014, Kumar and Carley 2016a). In this research, we propose a simulation test-bed to estimate the impact of such attacks.

Because of the complexity of the Internet, simulating an Internet-scale network based attack is nearly infeasible. Most existing simulation environments are designed for small-scale tests and are usually conducted in a lab setting using a few systems. Results from a small-scale simulation may not be a good representation of the Internet scale problem. The complexity is two-fold. First, it's hard to model agents that could resemble modern computer systems, but at the same time consume reasonable computing resources for a large-scale simulation. Second, openly available information on the Internet infrastructure is limited. Fortunately, we can endeavor to overcome both the problems. For a network-based attack like DDoS, we

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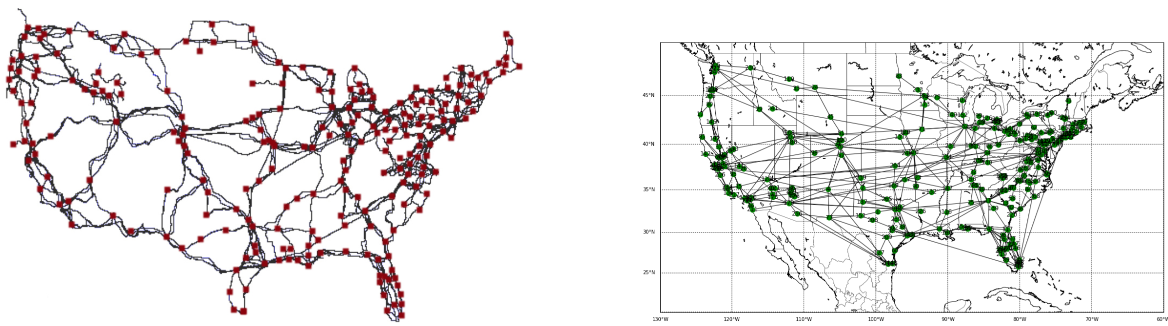


(a) The location of physical conduits. Adapted from Durairajan, Barford, Sommers, and Willinger (2015) with permission from the authors. Copyright 2015 by the Association for Computing Machinery.

(b) The network built using the physical conduits data (shown on the left). The green nodes are the IXPs located in different cities, and the conduits connecting them are modeled as straight edges.

Figure 1: The network designed to simulate attacks on the US Internet infrastructure.

can model the attackers and the target as dumb systems that can send and receive network packets. For the second limitation of modeling a close to the real Internet infrastructure, we apply recent development on mapping the optical fiber cables of the US. The mapping of the Internet infrastructure project (Durairajan et al. 2015) (see Fig.1a) has provided a practical knowledge of the US cyber infrastructure. By combining the cyber-infrastructure data with data on the Internet adoption by countries (Whitehouse.gov 2016), a simulation environment could be built to model a real attack environment. Our simulation environment allows to evaluate different attack scenarios and providing information on average degradation of the quality-of-service, and the approximate number of users impacted.

The important contributions of this research are: a) We design a simulation testbed mirroring the fiber-optics Internet architecture of the US. To the best of our knowledge, this is the first work that simulates DDoS attacks on a realistic US cyber infrastructure. b) We present a model to estimate the degradation in the quality-of-service and the number of users impacted in different attack scenarios. To make our simulation more realistic, we use a dynamic packet flow algorithm that changes the Internet traffic flow pattern with congestion. c) Our model enables to find cyber installations that are more vulnerable to attacks. We believe our approach could be useful to cyber-infrastructure companies and the Homeland Security.

The rest of this paper is organized as follows. Section 2 presents related work. We introduce the methodology of the simulation in section 3. In section 4, we model and discuss the experiments. The results of the experiments are presented in section 5, along with a discussion on the outcomes of the simulations. Limitations of our approach are described in section 6. We finally conclude and discuss future work in section 7.

2 RELATED WORK

Prior work on using simulation to model cyber-attacks can be grouped in two categories: a) Measuring resiliency of the Internet infrastructure b) Simulation of network based attacks.

2.1 Measuring Resiliency of the Internet Infrastructure

To explore the node to node resiliency of the global Internet infrastructure to under-sea cables physical damage, Omer et al. (2009b) and Omer et al. (2009a) modeled the Internet resiliency as a network optimization problem. The authors solved it using linear and mixed integer programming with constraints. Since most cyber-attacks don't entirely stop the flow of network packets but rather makes the Internet slower, this model is not best suitable for simulating DDoS attacks. Moreover this model did not account for the dynamic nature of the path used by Internet traffic, which is included in our model. In this research, we are interested in resiliency, but we don't model physical damage to the under-sea cables.

2.2 Simulation of Network Based Attacks

A number of researchers (Kotenko and Ulanov 2005, Kotenko 2005, Kotenko and Ulanov 2006, Li et al. 2008, Zhang et al. 2008, Qwasmi et al. 2011, Grunewald et al. 2011) have simulated DDoS attacks, albeit on a much smaller scale. Computer-systems are complex, and modeling their behavior makes agents complex and resource intensive which limits the scale of simulation. For example, Kotenko and Ulanov (2005) investigated different attack scenarios and protection mechanisms for networks with a variety of structures and security policies, and used OMNeT++ INET Framework for their development. The relative complexity of these models render them limited to small scale, with limited number of systems. If an agent is complex, it takes more computer memory to create and execute the simulation. We resolve this problem by proposing very simple agents, with only limited networking (send and receive data) capability. The study by Kong et al. (2003) is the closest to our research. In this work, Kong et al. (2003) modeled general flow of computer network using NS2 based simulation engine. The simulator creates Internet traffic from regular systems (not infected) as Pareto distribution, and traffic from bot systems as uniform distribution. In evaluation, they present how changes in source-network and sink-network affect the quality of services on the network. However, their network is randomly generated and hence does not reflect the reality. Simulating network flow on the realistic Internet network topology of the US, is one of our important contributions.

Another research area that is close to this research is the traffic simulation problem. Balmer, Cetin, Nagel, and Raney (2004) used multi-agent simulations to model a traffic problem. The design is not well aligned to test cyber-attacks considering the route that a packet takes is more complex than a highway traffic flow.

3 METHODOLOGY

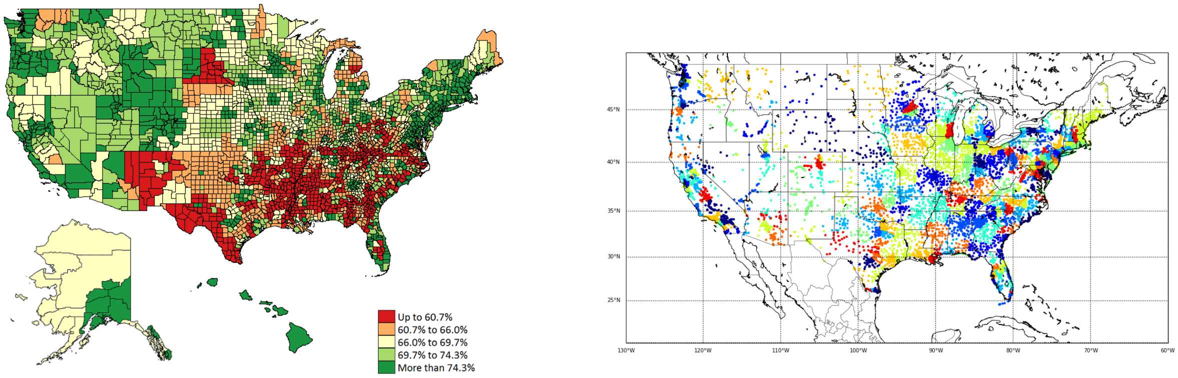
Distributed Denial of Service (DDoS) attacks are generally of two types a) Network-layer attacks b) Application layer attacks. In a network layer attack, the adversary exhausts the available network bandwidth of the service provider or the server, where as, in an application layer attack the goal is to overwhelm the processing capability of the target-server or router. In this study, we focus on network layer attacks. A network layer attack is based on the assumption that a company's network resources like firewalls, routers, and servers have limited capacity, which is based on the network requirements of the company. These requirements are determined based on average usage and are often not good enough to survive attack scenarios. The attacker's strength is decided by the number of the bots in control. During an attack, these botnets send a large number of network packets to saturate the limited bandwidth of the target company, so that genuine users are not able to access the services.

We use an agent-based network simulation approach to simulate cyber-attacks. Our simulation environment comprises of a network of connected Internet Exchange Points (IXPs) as nodes and Internet packet traffic as flow (see Fig. 1). We would like to clarify that the problem that we are solving is different from the network resiliency problem as solved in (Omer et al. 2009b, Omer et al. 2009a), and the network robustness problem as done in (Durairajan et al. 2015). The important difference is the dynamic nature of traffic in the Internet. In the Internet, the flow of packets change path as a portion on the Internet gets congested, and hence assuming the Internet network to be a static network is not right. In fact, two packets meant for the same target may take different routes. The dynamic nature of the Internet results in impacting users that are sometimes physically far away from the actual attack target.

In this section, we present the agent model, the simulation environment model, the flow model and approximations used, our problem formulation and the pseudo code for simulation.

3.1 Agent Modeling

We use an agent-based model for this simulation. We model computer-systems as active agents, and the fiber-optics network as a passive environment. For simplicity, an agent is any system (including laptops,



(a) Internet adoption in the US by county.

(b) The generated computer density map.

Figure 2: The computer distribution used in our study is generated from population density distribution and Internet adoption map (2013 census). In the right image, computers are grouped by connecting them to the nearest IXP. Groups are visualized in different colors.

mobile devices, Internet of Things, and Servers) that is connected to the Internet. Agents can act both as source or sink of packets, and to simulate a more realistic environment both the source and the sink have limited bandwidth. Flow through links also have a bandwidth limitation. In simulation, source agents send packets that travel from source to target (sink).

We have two types of agents. First agent type is 'Un-compromised Agents' i.e. the systems that are not compromised. The second agent type is bots, i.e. the systems that are compromised and are used in attacks. For location of 'un-compromosed agents' we use the data from US census on population and percentage population with active Internet connection (Fig. 2a). For location of botnets (infected computers), we us botnet tracker data from Malwaretech website (Malwaretech 2016). Since we know the approximate location of each of the agents (shared by Malwaretech), we could approximate the route the packets from an agent could take to reach a target (explained later). We can do the same for all bots, to understand the network congestion these bots can create.

3.2 Environment Modeling

We used systems as agents to simulate the DDoS cyber attacks on the US Internet infrastructure. The environment in our case is the network generated by the optical fiber cables and the Internet exchange points (IXP). We model it as a network with nodes and links. Nodes represent the IXPs and links are optical cables connecting different IXPs. We use optical-fibers data from Durairajan et al. (2015) for modeling the links. Figure 1b shows the network built using nodes and edges data. The authors shared their data on nodes, and their connections between cities (Fig: 1a), but they do not have data on bandwidth capacity of these optical fibers. We approximate the bandwidth limitation of the long-haul pipes to 8 Tbps (Betker et al. 2014).

3.3 Flow Modelling

An attack scenario is modeled as flow of large traffic to a target node. We first estimate the regular traffic flow in the network without any attacks using computer density distribution. For estimating the attack traffic, we first pick an attack target, and direct all bots to send data packets to the target. We then superimpose the attack traffic on the regular traffic. In our experimental attack scenarios, We use the information on the bots locations shared by a security website (Malwaretech 2016) to find the nearest IXP for all bots, and estimate the number for bots connected to each IXP (Fig. 3). The number of bots connected to each IXP allows to estimate of the attack-traffic that an IXP generates and adds to the Internet. After estimating the attack-traffic, we remove the bots from the simulation and only keep the IXPs with equivalent bots load. This way we avoid the complexity of using millions of systems in the simulation, but still use their attack impact. The superposition of attack traffic on regular traffic creates a congestion map of the entire network, and allows us to measure the drop in average quality-of-service. We also estimate the number of users impacted, which is indirectly approximated by the number of users connected to each IXP (Fig. 3b) and the estimate of congestion at each IXP.

3.3.1 Simplified Model of Packet Flow on the Internet

Because the Internet is very complex with billions on systems and millions of routers, simulating an attack with so many components is unrealistic. We simplify the packet flow architecture such the simplified model contains the necessary characteristics needed for a realistic simulation. Figure 3 shows a simplified version of packet flow through the Internet that has been used in this work. In the figure, compromised systems (shown in light yellow) send a stream of packets to a target system (shown in red). As the compromised systems (bots) send packets at the same time, the packet flow (shown as purple arrows) adds up as the flow moves towards the target. To keep the simulation simple, we have entirely removed the systems by their contribution made to an IXP (shown in the right image). This simplification is possible because the number of systems connected to an IXP does not change dynamically (on an average) and hence the network topology is mostly static (flow is not). To summarize, we replace all systems with their weight on the nearest IXP, similarly we replace all bots with their equivalent weight on the nearest IXP. The count of bots and systems connected to an IXP enables us to estimate the attack traffic the IXP can generate, and also allows to estimate the number of users that get impacted when an IXP is congested.

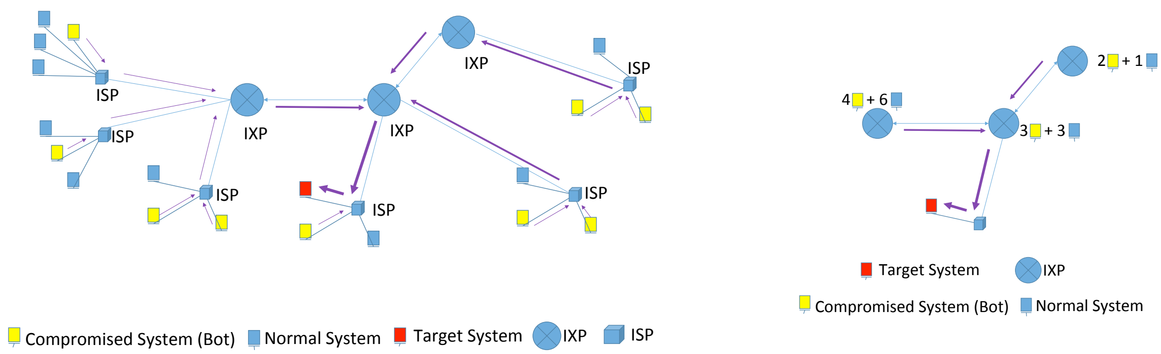


Figure 3: A Network flow representing an attack scenario. Left figure shows a scenario in which the red node is the target of attack. Yellow nodes are bots or attacking systems that generate network flow (traffic). Purple arrows show the direction of traffic flow, and the width of arrows shows the volume of traffic. Figure on the right is a simplified version on the left network, where we have replaced the individual systems by their counts on IXPs as attributes. The simplification speeds up the network simulation as the simplified network only includes IXPs (with equivalent system weights) and a target.

3.3.2 Approximating the Congestion Control Algorithms Used on the Internet

We approximate the Border Gateway Protocol (BGP) algorithms commonly used by gateway routers by Dijkstra's shortest path algorithm (Dijkstra 1959). BGP is commonly used as the protocol between Internet service providers and is designed for packets to take the most efficient route. In simple terms, BGP uses cost metrics for each path to find the most optimum path, which also makes it complex. To keep the simulation simple, but still include the impact of cost of traversal through congested paths, we used Dijkstra's shortest path algorithm, where cost in a path is determined by the congestion in the path. Including Dijkstra's algorithm makes the simulation dynamic and more realistic, e.g. as we increase the attack bandwidth sent by a bot, the packets are likely to take different paths, and hence creates congestion in other paths influencing the quality of service in areas which may not be close to the target.

3.4 Problem Formulation

Given a flow network $G = (V,E)$, many non-negative sources $f : (V_i) \to Z+$, a negative sink $h : (V_j) \to z-$, links with limited capacity $E_i(V_i,V_j) < E_(max)$, there exists a equilibrium state of flow using any weighted shortest path algorithm. U_i is the number of systems (or users) connected to V_i (IXP) which is determined by the systems density map (Fig. 2b), where users ($U \sim$ User Density) grouped to nearest node (explained in Fig. 3). Similarly $B_i \propto f : (V_i)$ is the number of bots connected to V_i (IXP). Here B_i is determined by bots density data from Malwaretech (Malwaretech 2016) grouped by nearest node (IXP). The equilibrium state allows estimation of congestion at each node C_i, which enables to estimate the number of users impacted $\sum_i U_i$. To estimate $f : (V_i)$, i.e. the flow generated by node V_i (an IXP), we use bot density function ($B \sim$ Bot Density), and group the bots to their nearest node which implies B_i is the total number of bots connected to i^{th} node. To estimate the number of users impacted ($U_{impacted}$), we sum the number of users $\sum_i U_i$ connected to i^{th} congested node. Given an attack target, the average reduction in quality of service could be measured by estimating the congestion in the network, which could be approximated by $\sum_{i,j} E(V_i,V_j)_{avg} / \sum_{i,j} E(V_i,V_j)_{congestion}$. In an attack situation, the users trying to access the targeted server (or IXP) get impacted the most. Also the users connected to other nodes experiencing congestion get impacted. We estimate the number of users impacted by counting all the users connected to the congested IXPs ($U_{impacted} = \sum_{i \in c} U_i$, where c is the set of congested nodes). Given an attack scenario with an attack target, we measure the trend of 'number of users' impacted, with increase in attack bandwidth (e.g. each infected system sends attack bandwidth from 1 Mbps to 5 Mbps) (see Algorithm 1). Source code to reproduce similar experiments can be obtained by requesting the first author.

3.5 Virtual Experiment

Table: 1 summarizes the variables used in the experiment. We have two parameters in the model, a target and the bandwidth of attack initiated by each bot. The constants are maps that we obtained from different data sources including 'optical-cable' map from Durairajan et al. (2015), population and computer ownership from census, and map of Mirai botnet (Malwaretech 2016). The output variables are the number of users that get impacted in an attack scenario, and the degradation on QoS (sometimes referred as congestion). To validate, we used the data from downdetector website.

4 EXPERIMENTS

Our experiment has different scenarios, and each scenario has a target. Though it is possible to use multiple targets, to keep the results easy to understand, we have used a single target in each scenario. For example, we can pick a server hosted in New York city as an attack target, and simulate the experiment. In any experiment, we generate network traffic from all nodes (except the target node) directed towards the chosen target. The simulation will result in a map of users that get impacted because of attack on the target. We can also determine the trend the number of users that get impacted as the attack bandwidth (by each bot) is varied. Besides, we can also estimate the average degradation (using congestion in the network) in the quality of service with the increase in attack bandwidth. We simulated two different attack scenarios and estimated the impact of attacks.

4.1 Scenario 1 - Attack on Dyn Inc on 21st of Oct, 2016

Targeting a server hosted in New York City, we try to mimic the attack on DYN Inc (DYN INC 2016). In this attack simulation, all bots target the New York city server. Since Downdetector website (http://downdetector.com/) provides data on how people in different regions got impacted because of

Algorithm 1: Pseudo Code to Estimate the Number of Users Impacted

```
Data: Network H, Target target, UsersAtEachIXP usersIXP
Result: Number of Users Impacted in Each Iteration
impactedUsers = []
while i < numberOfIterations do
    for node ∈ H.nodes() do
        if node is not Target then
            /* Find weighted shortest path from source to target using Dijkastra algorithm*/
            path = dijkastraPath(H, node, target)
            for edge ∈ path do
                /*Increase flow in edge*/
                H.currentFlowBandwidth[edge] += attackBandwidthIncrement
                /*Update flow through each ixp in the path*/
            end
        end
    end

    numberOfUsersImpacted = 0
    for ixp ∈ H.ixps() do
        if ixp.flow ≥ maxCapacityOfIXP then
            /* Increase number of users impacted by the number of users connected to IXP */
            numberOfUsersImpacted+ = ixp.users
        end
    end
    impactedUsers ⟵ numberOfUsersImpacted
    i++
end
```

the DYN attack, this attack could be used to approximately validate the simulation. Note that the attack on Dyn Inc. is more complex than just a simple DDoS attack as the attack was done in three waves and the target of attack varied throughout the day. However, because of absence of data on the location of the exact server that was attacked in each wave, we assume the New York server to be the only target. Even with this simplification, we get a close estimate of users impacted by this attack.

4.2 Scenario 2 - Attack on AT&T on 28th of Oct, 2016

In this scenario, we try to model an attack on the AT&T Internet infrastructure in the Chicago area. This scenario attempts to model the network outage reported by Downdetector website (http://downdetector.com/) on 28th of October 2016. The exact cause of the problem with AT&T servers is unknown, but a visualization map of the users impacted was obtained from the website.

In the next section, we describe the results obtained for each of the experiments.

5 RESULTS AND DISCUSSIONS

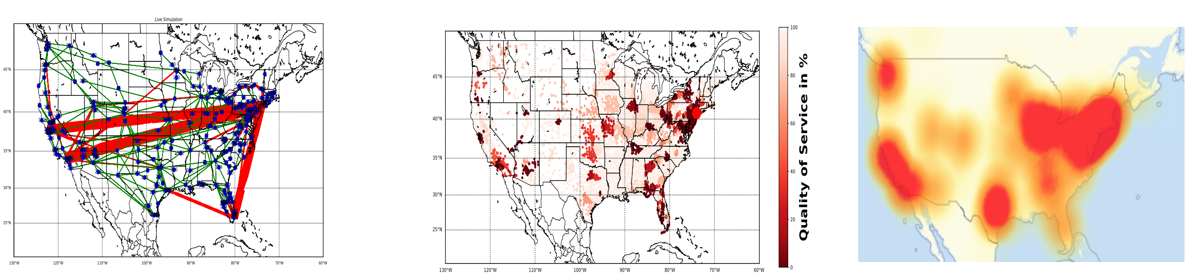
In this section, we present the simulation results for the two attack scenarios, and compare them with their known impact map for validation. We also describe the impact of those attacks on the Quality of Service (QoS).

Table 1: Virtual Experiment Table

Factors	Values	# of Values
Inputs		
Attack Target (A web-server or an IXP)	One of the nodes in the Network	1
Bandwidth of Attack	1 to 5 Mbps per bot	10
Constants		
Long-haul optical-fiber Map	Map from (Durairajan et al. 2015)	
Population density	Number from census	
Computer Ownership	Percentage from census	
Map of Botnets	Mirai Bot family from (Malwaretech 2016)	
Outcomes		
Number of Users Impacted	In thousands	
Degradation in Quality of Service	Percentage	1-100
Validation		
AT&T Attack on 28th of Oct, 2016	Map of Impacted Users	
DYN Attack on 21st of Oct, 2016	Map of Impacted Users	

5.1 Scenario 1 - Attack on Dyn Inc. on 21st of Oct, 2016

In scenario 1, we use a server linked to the New York city IXP as the target of attack. The attack tries to simulate the DYN server attack that happened on Oct 21, 2016. We first discuss the congestion in the fiber-optics cables as observed in the simulation (Fig. 4a). In Fig. 4a, the width of edges indicate the network flow through the optical fibers, and the color indicates the congestion level. As the bandwidth of attack is increased in each iteration, more and more edges (optical-fibers) showed congestion. This is as expected in an attack. However, the edges that got more congested were not always close to the target. In fact, two of the most congested links are actually connecting the west coast areas, and one of the links is connecting the southern part of the US. This is a result of the dynamic nature of simulation. Because Dijkstra's shortest path algorithm chooses path with the least cost from a source to a target, this changes the packet flow routes as current routes get more congested. Moreover, we can see that the most congested links are mostly linking high density areas and are long-haul links. This can be explained by the fact that these long haul links are likely to be the best route from far-off areas, as the length of optic-fibers do not affect the edge weight.



(a) Simulation Scenario 1: Visualizing the congestion in the network while an attack on the DNC INC New York city service.

(b) Simulation result for attack. The color bar indicates the relative impact in different areas.

(c) Actual impact as reported by DownDetector website. The red areas are most adversely impacted.

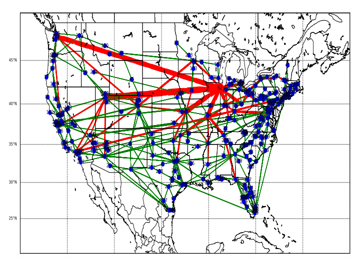
Figure 4: DYN attack Simulation: For DYN outage on 21th Oct, we compare the result of simulation to actual impact as reported by DownDetector website.

Figure 4b shows the result of the final stage of simulation (max bandwidth of attack). In Fig. 4c, we show the actual impact as reported by downdetector website. The image was downloaded from wikipedia, and shows the impact of the DYN attack as measured by 'downdetector.com'. The red areas are most adversely impacted regions. The image shows that the east coast of the US was primarily impacted because of the attack, but outages were also recorded in some western and southern parts of the US. If we compare the simulation result (Fig. 4b) and the actual impact (Fig. 4c), we can observe that both of them highlight the eastern areas as mostly impacted. This is expected as the target of the attack was based in the New York city. What is interesting to see that some areas in the central, and western parts of the US were impacted, and the simulation also predicted similar areas.

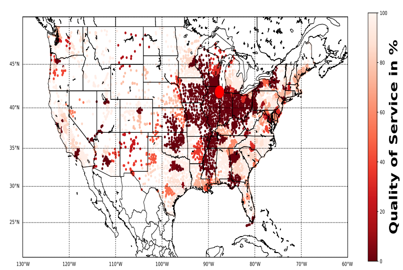
Lastly, we use the trend plot (Fig. 6a) to discuss the percentage of users impacted, and how the number changes with increase in the bandwidth of attacks. As we can observe, the increase is steeper in the beginning but the rate of increase slows down with increase in attack. The plot of the users impacted is based on the estimation of the users who are actively connecting to the attacked server.

5.2 Scenario 2 - Attack on AT&T on 28th of Oct, 2016

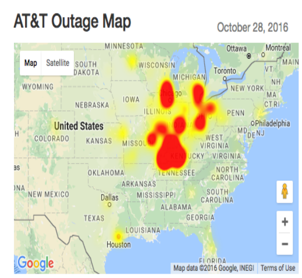
In scenario 2, we use Chicago city AT&T server as the target of attack. The attack tries to mirror the AT&T server problem that happened on Oct 28, 2016. We first discuss the congestion in the fiber-optics cables as observed in the simulation (Fig. 5a). As described earlier, the width of edges indicate the network flow through an optical pipe, and the color indicates congestion level. As the bandwidth of attack is increased in each iteration, more and more optical-fibers (edges) registered congestion. Figure 5b shows the result of the final stage of simulation.



(a) Simulation Scenario 2: Visualizing the congestion in the network while attack on a server in Chicago. Red lines are the congested routes.



(b) Simulation result of degradation in the quality of service by an attack on a server connected to Chicago IXP . More red is more severe.



(c) Actual impact as reported by DownDetector website. The red areas are more adversely impacted regions.

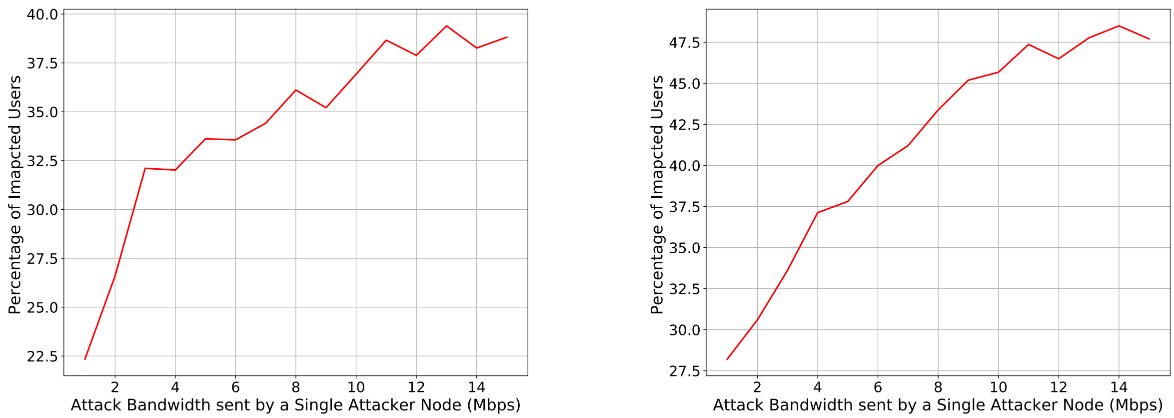
Figure 5: AT&T attack Simulation: For the AT&T outage on 28th Oct, we compare the result of simulating an attack on a server connected to Chicago IXP to actual impact as reported by DownDetector website.

In Fig. 5c, we show the actual impact as reported by downdetector website. The image was obtained from 'downdetector.com' website. The red areas are most adversely impacted regions. The image shows that areas near Chicago and south of Chicago were mostly impacted because of the attack, but minor outages were also recorded in some far areas. If we compare the simulation result (Fig. 5b) and the actual impact (Fig. 5c), we can observe that both of them highlight similar areas as the one primarily impacted. The QoS not only degraded near the Chicago city but also in some areas far away.

Figure 6b shows the trend of 'percentage of users' impacted as the bandwidth of attack was increased assuming assuming these users were actively trying connect to the server. As we can observe, the increase is steeper in the beginning but the rate of increase slows down and converges.

If we compare the result of attack on 'New York IXP' to the result of attack on 'Chicago IXP', we find that the plot of 'number of users' impacted is more steep in case of the attack on the 'New York IXP'.

There could be many reason for this like the density of population around the New York city is higher compared to density of population near Chicago, especially on the western sides of Chicago.



(a) Simulation Result for attack on DNC server in the city of New York.

(b) Simulation Result for attack on AT&T server in Chicago.

Figure 6: The plots show the trend of users (actively trying to connect) impacted with increase in attacks bandwidth.

6 LIMITATIONS

We designed a simple network simulation model for DDoS, yet sophisticated enough, to mimic complex nature of cyber-attacks. The benefit of simplicity is that we can efficiently simulate attacks that are generated by millions of systems. To keep the model simple yet realistic, we have made a few assumptions. First, The Quality of Service (QoS) as observed by a user is determined by the congestion of traffic at the nearest IXP. This may not always be true, especially when the traffic is local to an ISP, e.g. a client is watching video streaming data from a server located in proximity. In some other cases, rather than passing through nearest IXP for all their traffic flow, ISPs engage in peering. Second, we approximate the botnet data from the Mirai botnet population obtained from a website (Malwaretech 2016), which may or many not be an accurate representation for many attacks. Mirai has recently initiated only some of the known attacks. Also, these botnets have a dynamic nature, so they may grow or reduce in size with time. All these factors limit our estimations. Third, we assumed that the bot locations are known and do not vary. In reality, bots become alive when an infected system connects to the Internet (i.e. switched on) and disappear when the system is disconnected (i.e. switched off). Finally, we used Dijkstra's shortest path algorithm for path estimation, which is again a crude approximation of the BGP routing algorithm used on the Internet.

7 CONCLUSIONS

In this research, we designed and implemented a network simulation model to understand the Internet traffic flow pattern in a DDoS attack situation. To keep the simulation simple, yet mirror the complexity of the Internet, we made certain assumptions that were reasonably justified. In particular, we combined all bots and systems connected to an IXP as one node, which allowed us to approximate the amount of attack traffic a node can generate, and the number of systems impacted if a node is experiencing traffic congestion. To approximate the traffic generated by bots, we used bots data from a security website, and to approximate the number of systems connected to an IXP, we used population density and the Internet penetration survey data. To make our network test environment more realistic, we used the fiber-optics map of the US from a recent research study. Using this novel network simulation test-bed, we simulated results for two different attack scenarios to understand the traffic flow as a function of attack-bandwidth. The traffic flow visualization enabled us to find the edges (fiber-optic cables) that are more prone to congestion in case of an attack. We also used real data from downdetector.com website to compare both simulation results and found a reasonably good similarity. We provided a list of assumptions that limit our study, but we hope that the approach we have used could be used by the Internet Infrastructure companies or the Homeland Security to better understand the Internet infrastructure vulnerabilities of the US.

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AUTHOR BIOGRAPHIES

SUMEET KUMAR is a PhD student in the Institute for Software Research at Carnegie Mellon University. He is interested in cyber security, machine learning and dynamic network analysis. He received an MS degree in Software Engineering from Carnegie Mellon University in 2013, and a B.Tech in Aerospace Engineering from the Indian Institute of Technology Kanpur (IIT Kanpur) in 2007. His email address is sumeetku@cs.cmu.edu.

KATHLEEN M. CARLEY is a professor in the School of Computer Science in the department - Institute for Software Research - at Carnegie Mellon University. She is the director of the Center for Computational Analysis of Social and Organizational Systems (CASOS), a university wide interdisciplinary center that brings together network analysis, computer science, and organization science. She and her lab have developed infrastructure tools for analyzing large scale dynamic networks and various multi-agent simulation systems. Her email address is kathleen.carley@cs.cmu.edu.