Effect of Malicious Traffic on the Network

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***Abstract*— The Internet has seen a continuous rise in malicious traffic including DDoS and worm attacks. In this paper, we study the effect of malicious traffic on the background traffic by gathering traces from two different locations. We show that the malicious traffic causes the increases of DNS latency by 230% and web latency by 30% even on highly over-provisioned links. Using a packet-level simulations based on an empirically derived model of the worm, we demonstrate that the effect of worm-infected hosts can be disastrous when they trigger a DDoS attack.**

I. Introduction

During the last few years, the Internet has witnessed a surge in *malicious traffic*, such as that generated by denial-of-service (DDoS) attacks and propagation of worm traffic [1]. Most previous work [1], [2], [3], [4], [5], [6], [7] has focused on studying the reasons behind the malicious traffic but not their effects on the normal background traffic. We define normal traffic as network traffic generated due to well-known services and applications, for example, web, ftp, nntp, and smtp.

In this paper, we study of the characteristics of network traffic during phases dominated by malicious behavior of DDoS attacks and worm propagation, and compare it with phases when such activity is negligible. We show that DDoS attacks causes DNS latencies to increase by 230%, and the web latencies to increase by 30%. We find that the attacks do not significantly affect the throughputs of bulk TCP transfer. We also present detailed analysis Linux Slapper Worm and study the worm activity in the network. We then use an empirical simulation model to predict the effect of worm traffic when the worm-infected hosts trigger a DDoS attack.

The main contribution of this paper is to provide a quantitative analysis of the background traffic in the presence of malicious activity. We quantitatively study the effects of DDoS attack and worm traffic on normal background traffic. Currently most backbone links are under-utilized [8]. One would expect that the malicious traffic such as DDoS attacks and worm traffic will not change the background traffic patterns significantly if the links are highly over-provisioned. However, we find that this is not completely true. This work motivates the need to study more closely the reasons behind these observations. We believe that there is a need to do further studies of router mechanisms that can give us better performance in the presence of malicious traffic.

II. Related work

Several researchers have previously studied DDoS attack detection and response, and worm traffic propagation. In this section we provide a brief overview of DDoS and worm related research and compare how this paper complements previous studies.

A. DDoS

DDoS attacks attempt to exhaust the resources of the victim. The resources may be network bandwidth, computing power or operating system data structures. Previous research on DDoS attacks focused on either detecting the attack [9], [2], [3], [4] or responding to the attack [10], [11], [12], [13], [14], [15], [16], [17], [18] by blocking attack packets.

Attack detection techniques can be either based on an *anomaly-detection* approach or a static *signature-scan* technique. A large number of anomaly-detection tools have been designed and implemented previously, such as NIDES [19], Emerald [20] and Bro [2]. Anomaly-detection first establishes a normal behavior pattern for users, programs or resources in the system, and then looks for deviation from this behavior. Some anomaly-detection techniques exploit the absence of correlation between bidirectional traffic to detect an attack [9], [4], [15]. On the other hand, signature-scan techniques passively monitor traffic seen on a network and detect an attack when patterns within the packet match predefined signatures in a database. Snort [21] is a popular signature-scan based attack detection tool. In this paper, we use an anomaly-detection technique that tracks the number of source connecting to a single destination. Traffic is flagged as an attack if there is an abnormally high number of source addresses connecting to a single destination address.

B. Worm Traffic

Moore et. al. [5] present analysis of backscatter data gathered during the CodeRed infection last July-August. The data indicates 395,000 computers were infected world-wide with the CodeRed worm and resulted in approximately $2.6 billion in damage. Wang et. al. [6] presents a simulation based study to identify characteristics of worm infection. They study the effect of different factors that can be used to detect and treat infections while they are underway, using hierarchical and clustered network topologies. Zou [7] provides a two-factor worm propagation model that matches well with the

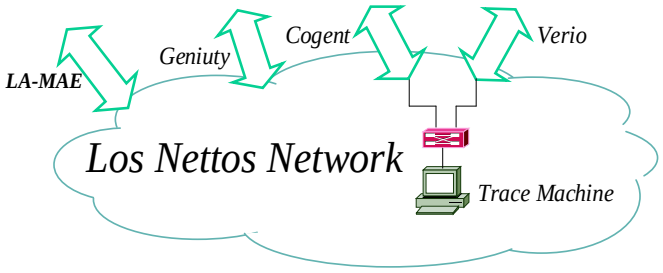


Fig. 1. The trace machine monitors two of the four peering links.

observed CodeRed data. It models human countermeasures like patching, filtering and decrease in infection rate as a function of time to explain the decrease in CodeRed scan attempts observed during the last several hours of July 19th. In this paper we attempt to analyze the Apache/mod_ssl worm and use an empirical simulation model to study the effect of a DDoS attack launched from worm-infected hosts.

C. Web traffic latency analysis

Barford et. al. [22] study various factors affecting the performance of HTTP transactions. They show that the server load affects the transfer time for small files, while network load affects the performance of large files. They also show that propagation delay plays a more important role than network variability, such as queuing, in affecting the performance of Web traffic. Our study complements previous work by demonstrating malicious traffic, such as DDoS attack and worm infections, can also significantly increase latency for small and medium web transactions.

III. Methodology

A. Trace collection

We collect traces from two different locations: one at Los Nettos [23], a regional area network in Los Angeles, and the other at the Internet2 [24] peering link at USC. We continously capture detailed packet level traces using tcpdump at both locations and test the presence of attacks or worm infections. The trace machines are Intel P4 1.8Ghz, 1GB of RAM running FreeBSD 4.5. We use a Netgear GA620 1000BT-SX NIC (Tigon II chipset) with a modified driver to supports partial packets transfer from the NIC card to the kernel.

Los Nettos has peering relationships with Verio, Cogent, Genuity, and the LA-Metropolitan Area Exchange as shown in the Figure 1 and serves a diverse clientele including academic institutes and corporations around the Los Angeles area. We monitor the Verio and Cogent peering links that experience an average utilization of 11% at 110Mbps and 38Kpps (packets-per-second). The kernel packet drops are below 0.04% during normal operation. During an attack, if packet rates exceed 100Kpps the drop rate increases to 0.6%. The USC trace machine monitors the Internet2 traffic to and from USC. The average utilization of link monitored by the trace machine is 6% at 60Mbps and 25Kpps.

Procotols	Los Nettos	USC
TCP	84.24%	95.61%
UDP	13.65%	4.102%
ICMP	1.216%	0.1182%
Other	0.8945%	0.1754%

TABLE I
PERCENTAGE OF PACKETS OBSERVED FOR EACH PROTOCOL AT LOS NETTOS AND USC

Service Protocols	Los Nettos	USC
http	39.445%	20.21%
ftp	0.5771%	0.1163%
dns	11.19%	0.2191%
smtp	2.190%	1.075%
nntp	1.584%	10.20%
ssh	0.2108%	1.102%
pop3	0.7342%	0.1186%
P2P	8.220%	15.22%
Games	0.4181%	1.637%
Other	35.43%	50.08%

TABLE II
PERCENTAGE OF PACKETS OBSERVED FOR EACH APPLICATION AT LOS NETTOS AND USC

The captured packet headers are analyzed offline to determine if there was an attack in progress. The detection script flags packets as attack packets if a large number of source IPs connect to the same destination IP within one second. Manual verification is then performed to confirm the presence of an attack. We experience a false positive rate of 25–35%; in other words, those packets have been flagged by the detection script but do not contain an attack after manual examination. A large number of false positives are generated due to network/port scaning and database updates between servers.

B. Metrics

We looked at several metrics to understand the impact of malicious traffic such as DDoS and worm on the network.

For web flows, we focus on flows with medium/small size (less than 100KB) to understand the impact of malicious traffic on the short-lived transactions. We analyze TCP flows larger than 100KB to understand the impact on bulk transfer. We also investigate the impact on the DNS lookup latency. DNS lookup latency is defined as the time lapse between the client sending out a request to the DNS sever and the client finally receiving an answer from a DNS server that terminates the lookup, by returning either the requested name-to-IP mapping or an error indication. To extract the statistics about lookup latency, we adopt similar approach as used in previous study [25].

IV. Traffic characterization

In this section we characterize the observed background traffic from traces at the two observation points and provide information regarding the captured DoS and worm traffic.

A. Background Traffic

Table I and Table II describe the composition of traffic seen at 2pm at both the trace locations The two locations have very different content at both, the protocol and the application level, permitting the study of malicious traffic on different traffic mixes.

We observe 13% UDP traffic at Los Nettos since it hosts a DNS root server. Further web traffic constitutes 40% of the observed traffic followed by 11% DNS traffic. At USC's Internet2 link, 95% of the network traffic is TCP. We could not classify a large percentage of the traffic since the Internet2 is extensively used for research and most of the packets uses ephemeral ports.

B. DDoS traffic

We have captured 90 DDoS attacks from 15 July to 15 Nov 2002. In this study we analyze change in latencies during an attack and hence require aggregate traffic traces from before and after the attack. Therefore this paper analyzes eighteen such attacks. Most of these attacks have significant impact on the background network traffic. In this section, we show the detailed packet and byte rates for one DoS attack and summarize characteristics of the remaining eighteen attacks. Section V discusses the effect of DoS attacks on the aggregate background traffic.

Figure 2 illustrates the change in aggreate traffic per second as the attack progresses. This attack was detected at USC, and consists of twenty eight attackers generating 70Mbps and 90Kpps of attack traffic (a total 11M packets and 8.6Gb of traffic in 192 seconds) directed at a victim within USC. The attack packets are 60 bytes and have the protocol field in the IP header set to 255. As shown in Figure 2(b), the magnitude of attack traffic is about three times the normal background traffic in terms of packets. Figure 3 shows the distribution of RTT of the attackers. The attackers have relatively small RTT distribution (less than 120ms) from USC because all attackers are located at different universities in the US and are connected to USC with relatively high bandwidth and low delay links. The small RTT enables the attack traffic to reach its peak rate rapidly.

C. Worm traffic

Worm infection is on the rise. Worms like Code Red and Nimda can infect thousands of hosts within short periods of time and generate significant network traffic [26]. In this paper we study the effect of the Apache mod_ssl worm (aka the Slapper worm) on the network. Our findings suggest that although the Slapper worm did not increase the network traffic at USC or Los Nettos significantly, but when the worm-infected hosts trigger a DDoS attack, the effect can be disastrous.

The Slapper worm exploits a bug in Linux-based hosts running Apache web servers with mod_ssl module. During the infection process the worm places source code in the /tmp directory of the target host. The worm then scans for potentially vulnerable systems on port 80 using an invalid HTTP GET request. When a vulnerable Apache host is detected, the worm attempts to connect to the SSL service via port 443 in order to deliver the exploit code. If successful, a copy of the malicious source code is then placed on the victim, where the attacking system tries to compile and run it. Once infected, the victim begins scanning for the other hosts to continue the worm's propagation.

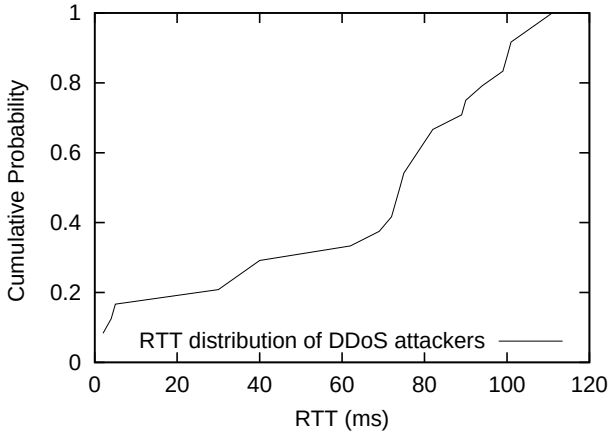


Fig. 3. RTT distribution of attackers

Top 10 Top-level Domains

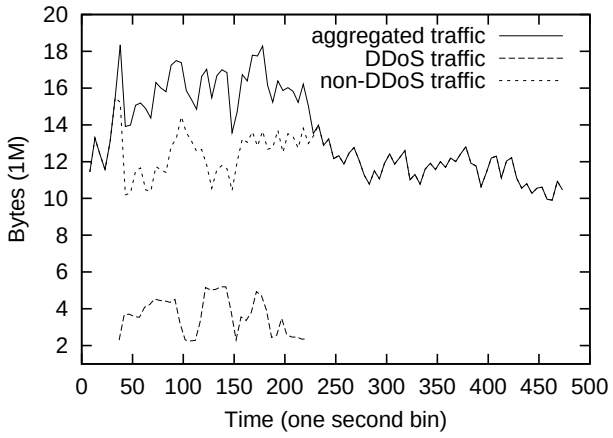
TLD	hosts	hosts(%)
unknown	858	31
net	447	16
com	330	12
us	173	6
ca	126	5
it	106	4
pl	104	4
edu	77	3
tw	70	3
mx	70	3

TABLE III
TOP TEN TOP-LEVEL DOMAINS WITH LINUX SLAPPER WORM INFECTED HOSTS ON OCT

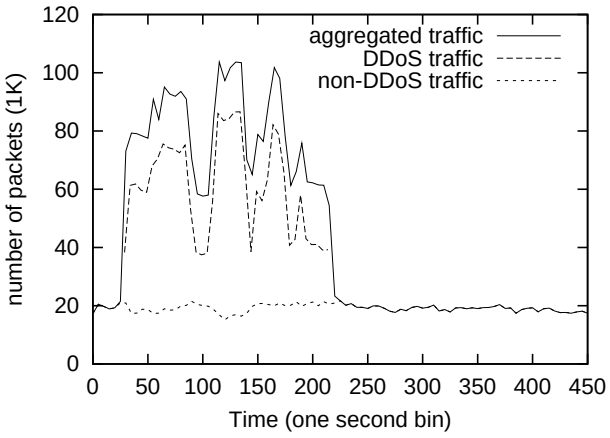
We observed a total 2727 infected hosts spanning over 39 AS domains distributed all over the world. Table III shows the distribution of the number of infected hosts from different domains. We see a large percentages of infected hosts are located in .net and .com domain. Note that we cannot determine about 30% hosts due to DNS name resolution failure. Figure 4 shows the distribution of the RTTs of the worm infected hosts. Unlike the RTT distribution of DDoS attack hosts, the RTT distribution of worm-infected hosts shows RTTs of over 1500ms. The huge diversity of RTT distribution suggests that if these worm-infected hosts generate DDoS attacks, they could potentially come from all over the world, making them harder to isolate.

V. EFFECT OF MALICIOUS TRAFFIC

In this section, we evaluate how malicious traffic changes observed traffic characteristics. Although it is intuitive that



(a) DDoS Traffi c volume in bytes



(b) DDoS Traffi c volume in packets

Fig. 2. The traffi c volume generated by DDoS attack in bytes and packets

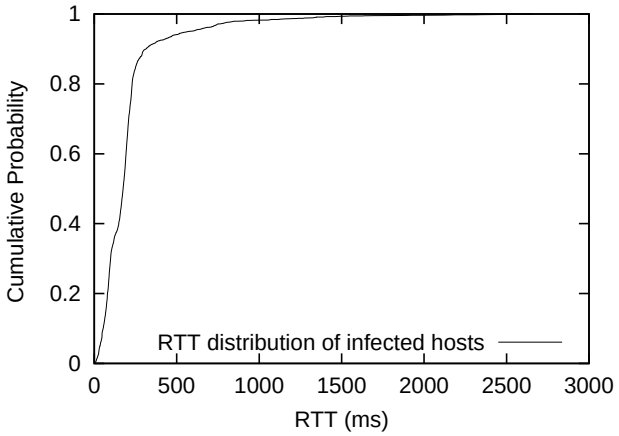


Fig. 4. RTT distribution of worm-infected hosts

traffic characteristics might change on a DDoS attack or a worm infection, we are not aware of any previous work that has quantitatively characterized the effect of such traffic. We observe an increases of 230% in DNS latency and 30% in web-latency during a DDoS attack. Further, based on an empirical simulation model of worm, we predict the effect of a DoS attack triggered by the worm-infected hosts.

A. DDoS traffic

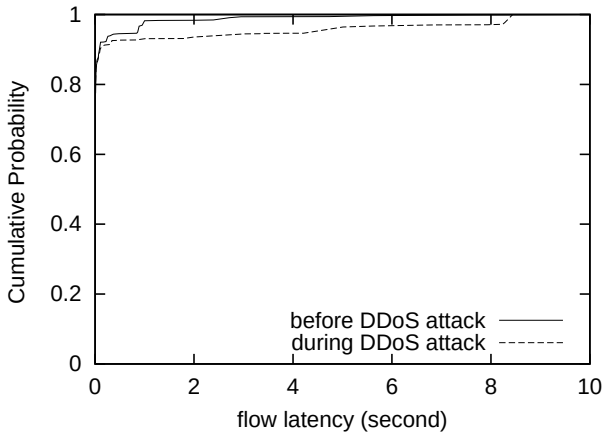
DNS latency is defined as the time elapse between the issue of a query to when the server returns an answer or a failure. The effectiveness of DNS strongly affects the performance of many popular network services such as Web traffic and Contents Distributed Networks (CDNs). In this section we first analyze the effect of an attack at Los Nettos and USC and then summarize the effect of all eigthteen attaks.

Figure 5 shows the change in latency at Los Nettos during a ping reflection attack [**?**]. This attack employes 145 distinct reflectors located in different countries like Brazil, Japan, Korea, Singapore, and United States generating attack rates of 4300pps. During the attack, we observe a 230% increase in the mean latency for DNS lookup, from 0.13s to 0.44s. We believe the sudden increase of traffic during an attack leads to higher average buffer occupancies at the routers, resulting in increased queuing delays. We also look at the effect of DDoS attack on web traffic, since such flows are more sensitive to the delay. We define web latency as the time lapse between the issue of HTTP request to the receiving of response data. As shown in Figure 5(b), the mean latency of web flows has increased from 9s to 11.9s, resulting in a 30% increase during the attack. Note that the DNS and web latencies increase even when the link is still under-utilized as shown in Section III-A.

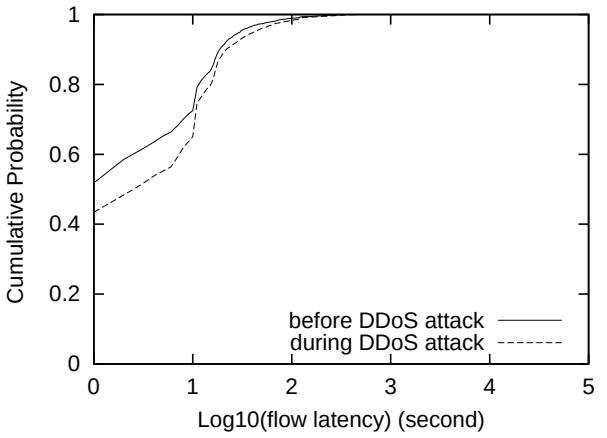
Next we observe the change in latencies during the attack captured at USC (discussed in Section IV-B). As shown in Figure 6(a), the mean latency of DNS lookup increases from 0.35s to 0.65s during the attack, resulting in a 85% increase in latency. Further, the mean latency for web flows increases from 7.2s to 8.8s, as shown in Figure 6(b), a 22% increase during the attack.

Even though the DNS and web latencies increases, we noticed that the mean throughput of bulk TCP transfers (which we define as flow size larger than 100KB), remains unchanged during the attack as indicated by Figure 7. We believe it is because the attack only last for only 192 seconds and has little effect on the long-lived TCP flows. As the attack duration increases, we expect to observe a change in latencies even in bulk TCP flows.

The change in latency during an attack is dependent on the intensity of the attack. To summarize the effect of different attack rates on the lantecy, we plot DNS and web latencies for all tweleve set of traces in Figure 8 and Figure 9. Figure 8 illustrates the DNS latency can increase as much as 250% during an attack, while while web latencies shown in Figure 9

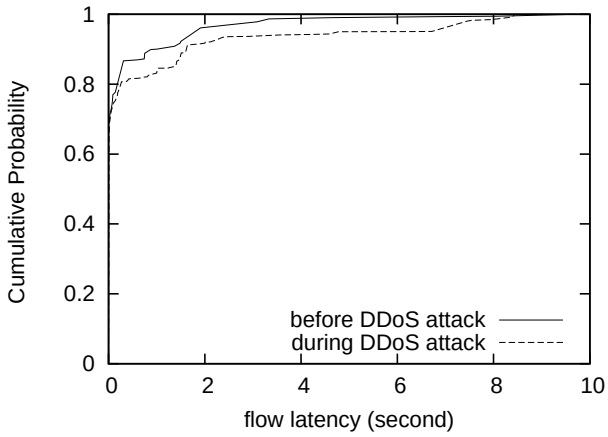


(a) DNS lookup latency increases by 230% during attack

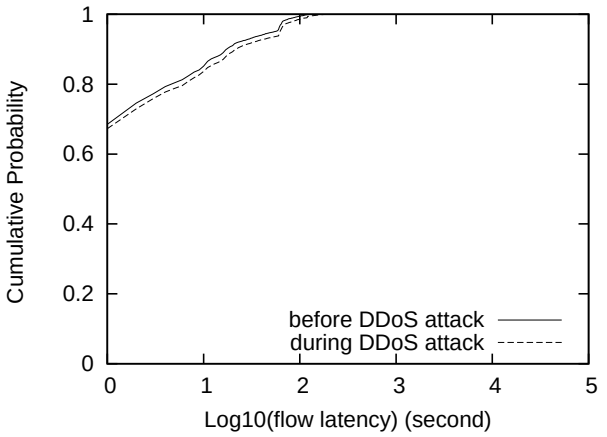


(b) Latency experienced by web fbws increases by 30% during attack

Fig. 5. Increase in DNS and web latency during DDoS attack at Los Nettos



(a) DNS lookup latency increases by 85% during attack



(b) Latency experienced by web fbws increases by 22% during attack

Fig. 6. Increase in DNS and web latency during DDoS attack at USC

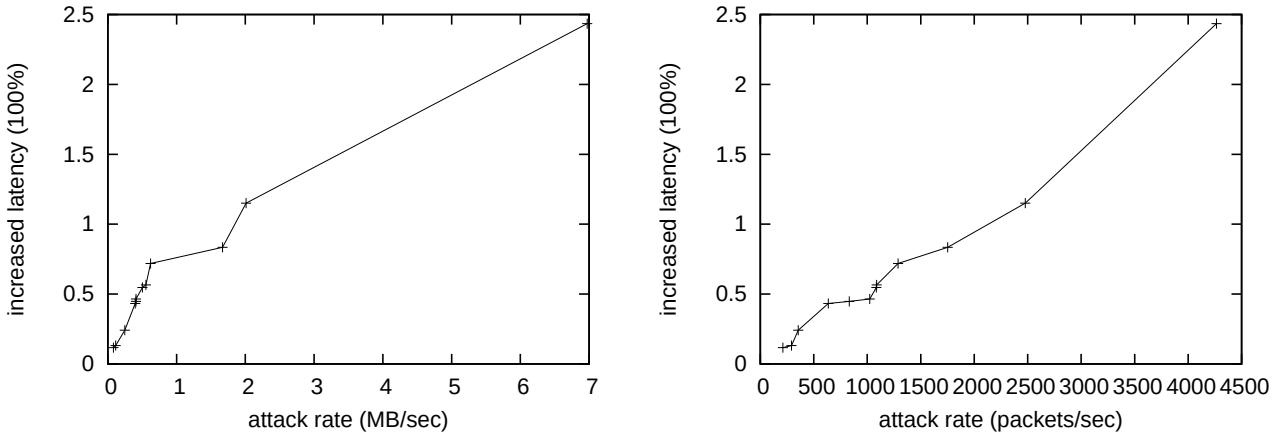
can increase as much as 40% as the attack rate increases. The traffic rate generated by most of the DDoS attack are less than 1MB/s. Note that the increase of DNS latency is more sensitive to the increase of attack rates (indicated by the steeper slope) since DNS requests are comparatively smaller than web flows.

The above results show that although short duration DDoS attacks might not be disruptive in terms of causing network failures and reducing aggregate throughput, the delay-sensitive traffic such as DNS and small/medium web transaction will still be affected by these attacks. Over-provisioning the links on the network does not provide the complete solution, since the short burst of DDos traffic can result in the increases in latency without affecting the throughput. We feel that the above observations can be used as hints to design better AQM mechanisms to provide differential services in order to protect short-lived traffic.

B. Worm traffic

The Slapper worm propagation did not generate disruptive amounts of traffic at our data collection point. However, if all the infected machines launched a coordinated DDoS attack, it would have a disastrous effect. In this section, we use hints from the collected Slapper worm data to determine the size of the compromised network. We study its effect on the network when all worm-infected hosts launch a coordinated DDoS attack using a ns-2 simulation.

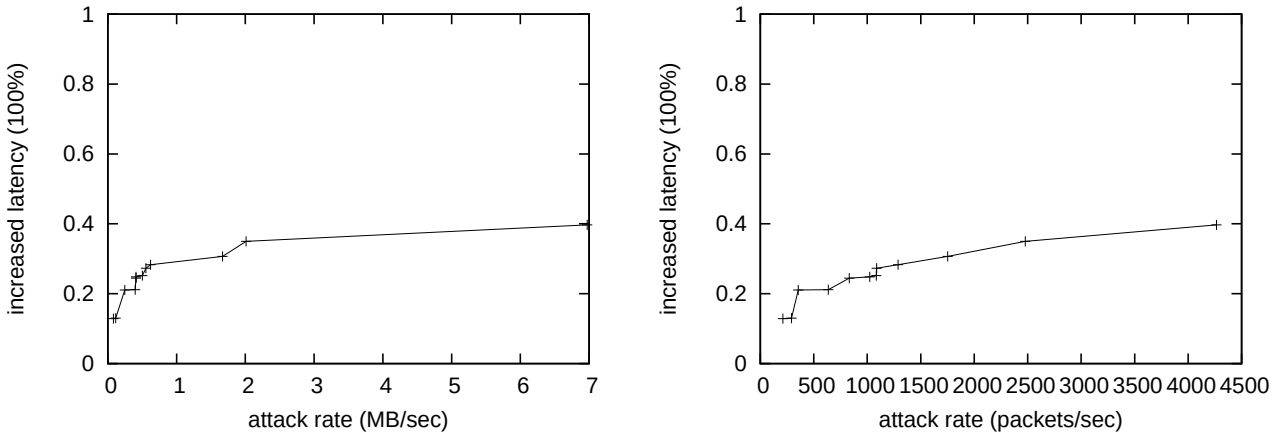
We derive the topology information of the worm-infected network based on the traces. We simulate its effect on the network when all worm-infected hosts launch a DDoS attack to a victim in the USC campus. We use a simple dumbbell topology with empirical distributions of RTT, flow rates and



(a) DDoS attack rate in bytes

(b) DDoS attack rate in packets

Fig. 8. Increased DNS lookup latency at different DDoS attack rates



(a) DDoS attack rate in bytes

(b) DDoS attack rate in packets

Fig. 9. Increased web latency at different DDoS attack rates

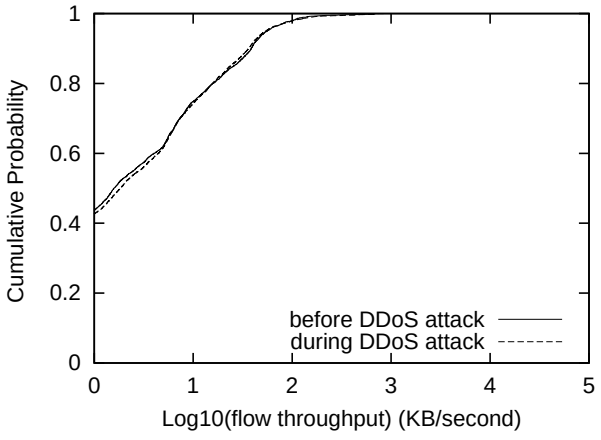


Fig. 7. Effect of DDoS attack on throughput of bulk TCP fbws

packet size derived from the traces. The DDoS traffic is modeled as constant bit rate source and currently no background traffic is simulated.

Figure 10 shows the attack intensity when generated by worm-infected hosts. We observed that the different RTT distributions of the attackers cause distinctively different transient ramp-up behavior before the steady state attack rate is achieved. Also when all the worm-infected hosts launch a DDoS attack, the average traffic generated due to the attack is fifty times larger than that generated by the DDoS attack that we traced.

VI. Conclusion and Future Work

In this paper, we present a detailed study of how the background traffic changes in the presence of malicious traffic. In particular, we show that the DNS latency increased by 230%

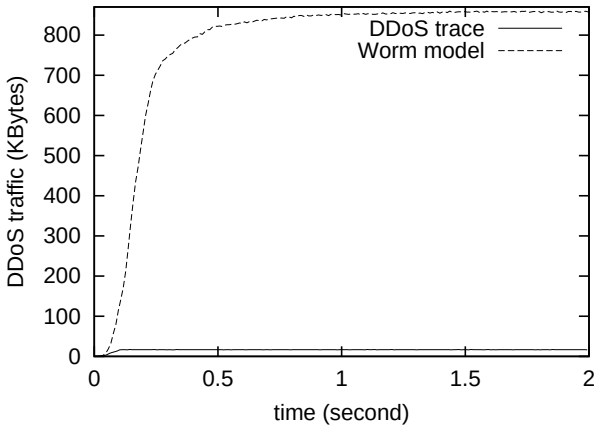


Fig. 10. Comparison of DDoS attack intensities; the DDoS attack and when an attack is launched by worm-infected hosts

and the web latency increased by 30% upon interaction with DDoS traffic. We also analyze the recent Linux Slapper Worm activity. Based on an empirical simulation model of worm, we predict its effect on the network when the worm-infected hosts trigger DDoS attacks.

This paper analyzes 12 attacks and presents analysis of change in latencies observed in the collected traces. We are currently working on a more detailed study of the effect of malicious traffic on background traffic by analyzing more DDoS and worm attacks. In particular, we are studying how different intensities and types of DDoS attacks will change the characteristics of the background traffic. Another aspect of our ongoing effort is to study various worm propagation models in order to predict the overall effect of worm traffic on the network.

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