Defending Against Distributed Denial-of-Service Attacks With Max-Min Fair Server-Centric Router Throttles

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***Abstract*—Our work targets a network architecture and accompanying algorithms for countering distributed denial-of-service (DDoS) attacks directed at an Internet server. The basic mechanism is for a server under stress to install a *router throttle* at selected upstream routers. The throttle can be the leaky-bucket rate at which a router can forward packets destined for the server. Hence, before aggressive packets can converge to overwhelm the server, participating routers *proactively* regulate the contributing packet rates to more moderate levels, thus forestalling an impending attack. In allocating the server capacity among the routers, we propose a notion of *level-k max-min fairness*. We first present a control-theoretic model to evaluate algorithm convergence under a varitey of system parameters. In addition, we present packet network simulation results using a realistic global network topology, and various models of good user and attacker distributions and behavior. Using a generator model of web requests parameterized by empirical data, we also evaluate the impact of throttling in protecting user access to a web server. First, for *aggressive* attackers, the throttle mechanism is highly effective in preferentially dropping attacker traffic over good user traffic. In particular, level-k max-min fairness gives better good-user protection than recursive pushback of max-min fair rate limits proposed in the literature. Second, throttling can regulate the experienced server load to below its design limit – in the presence of user dynamics – so that the server can remain operational during a DDoS attack. Lastly, we present implementation results of our prototype on a Pentium III/866 MHz machine. The results show that router throttling has low deployment overhead in time and memory.**

***Index Terms*—Congestion control, distributed denial of service, network security, router throttling.**

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I. INTRODUCTION

IN A DISTRIBUTED denial-of-service (DDoS) attack (e.g., [2], [3]), a cohort of malicious or compromised hosts (the "zombies") coordinate to send a large volume of aggregate traffic to a victim server. In such an episode, server resources are usually under much more stress than resources of the connecting network. There are two reasons. First, commercial servers are typically hosted by ISP's at web centers quite close to the backbone network with high capacity pipes. Second, the server will generally see the full force of the attack traffic, which has gone through aggregation inside the network. Hence, the server system can become totally incapacitated under extreme overload conditions.

We view DDoS attacks as a resource management problem. Our goal in this paper is to protect a server system from having to deal with excessive service request arrivals over a global network. (It is possible to generalize the approach to protecting an intermediate routing point under overload. However, implementation issues of having routers initiate control requests will then have to be addressed, which are not considered in the current paper.) To do so, we adopt a *proactive* approach: Before aggressive packets can converge to overwhelm a server, we ask routers along forwarding paths to regulate the contributing packet rates to more moderate levels, thus forestalling an impending attack. The basic mechanism is for a server under stress, say S, to install a *router throttle* at an upstream router several hops away. The throttle limits the rate at which packets destined for S will be forwarded by the router. Traffic that exceeds the rate limit can either be dropped or rerouted to an alternate server, although we will focus exclusively on the dropping solution in this paper.

A key element in the proposed defense system is to install appropriate throttling rates at the distributed routing points, such that, globally, S exports its full service capacity U_S to the network, but no more. The "appropriate" throttles should depend on the current demand distributions, and so must be negotiated dynamically between server and network. Our negotiation approach is *server-initiated*. A server operating below the designed load limit needs no protection, and need not install any router throttles. As server load increases and crosses the designed load limit U_S, however, the server may start to protect itself by installing and activating a rate throttle at a subset of its upstream routers. After that, if the current throttle fails to bring down the load at S to below U_S, then the throttle rate is reduced.[1] On the other hand, if the server load falls below a low-water mark L_S (where $L_S < U_S$), then the throttle rate is increased (i.e., relaxed). If an increase does not cause the load to significantly increase over some observation period, then the throttle is removed. The goal of the control algorithm is to keep the server load within $[L_S, U_S]$ whenever a throttle is in effect.

Router throttling has been implemented on the CROSS/Linux software router running on a Pentium III/864 MHz machine. Our implementation results indicate that (i) since throttling requires only looking up the IP destination address of a packet, it has essentially the same processing complexity as standard IP forwarding, and adds little computational overhead at a deployment router, and (ii) the amount of state information a router has to keep per throttle is a few bytes, for storing the destination IP address and the throttle value. Although throttling is space-efficient, the *total* amount of state information needed at a router is nevertheless linear in the number of installed throttles. Hence, it may not be possible for the routers to maintain state about *every* Internet server. However, the approach can be feasible as an on-demand and selective protection mechanism. The premise is that DDoS attacks are the exception rather than the norm. At any given time, we expect at most only a minor portion of the network to be under attack, while the majority remaining portion to be operating in "good health". Moreover, rogue attackers usually target "premium sites" with heavy customer utilization, presumably to cause maximal user disruptions and to generate the most publicity. These selected sites may then elect to protect themselves in the proposed architecture, possibly by paying for the offered services.

A. Our Contributions

Our contributions in this paper are:

- We contribute to the fundamental understanding of router throttling as a mechanism against DDoS attacks. In particular, we advance a control-theoretic model useful for understanding system behavior under a variety of parameters and operating conditions.
- We present an adaptive throttle algorithm that can effectively protect a server from resource overload, and increase the ability of good user traffic to arrive at the intended server.
- We show how max-min fairness can be achieved across a potentially large number of flows, and the implication of a notion of *level-* k *max-min fairness* on DDoS attacks.
- We study how throttling may impact real application performance. Specifically, we demonstrate via simulations the performance impact on an HTTP web server.
- We present system implementation results to quantify the deployment overhead of router throttling.

B. Paper Organization

The rest of this paper is organized as follows. In Section II, we discuss the practical challenges of deploying router throttling in the Internet. Our system model is introduced in Section III. In Section IV, we formally specify a baseline and a fair algorithm for computing throttle rates. In Section V, we present a control-theoretic mathematical model for understanding system performance under a variety of parameters and operating conditions. To further examine system performance under detailed packet network models, Section VI presents diverse ns2 simulation results using a realistic network topology. Implementation of router throttling on the CROSS/Linux software-programmable router, as well as its experimental evaluation, is presented in Section VII. Section VIII compares our solution approach with related work in the literature. Section IX concludes.

[1]Notice that *reducing* the throttle rate means *increasing* the extent of throttling, because a router will restrict more traffic destined for S.

II. Deployment Issues

The objective of our work is to explore some fundamental issues in mitigating DDoS attacks based on controlling aggressive network attackers. We focus on the dynamic resource control problem of giving good users productive access to a server's resources in spite of excessive demands from the attackers. We do not claim to present a complete DDoS solution in the present work. In particular, while our results are promising, several deployment issues will have to be resolved to bring the solution approach to bear in practice. These issues, discussed below, are challenging and beyond the scope of this work.

First, our trust model is that routers in the defense network trust each other, but they do not necessarily trust the network users. In particular, these users may spoof packets, disobey congestion signals, initiate bogus network requests, etc. As we push the "defense perimeter" further away from the server to be protected, requests to install router throttles are more likely to cross multiple administrative domains. Establishing trust relationships between the different domains, such that requests originating from one domain will also be honored in the other domains, is challenging and not addressed in the present work. Second, our approach is most useful under the assumption that attackers are significantly more aggressive than regular users. If the assumption is not true, good user traffic can be penalized to a comparable extent as attacker traffic. Our solution is then mainly useful in ensuring that a server under attack can remain functional within the engineered load limits. However, it does require more effort on the part of a malicious entity to assemble a large number of attack machines each behaving as a regular machine.

Third, since attackers can be highly unpredictable, it is inherently difficult to exhaustively model attacker behavior using only simulation experiments. In view of the problem, we have developed an analytical model that allows us to more basically and systematically study the behavior of our control strategy. Our model brings forth several control parameters that will affect system performance of stability and convergence speed. Currently, these parameters must be chosen based on estimates of the operating conditions and user policies to balance system stability versus responsiveness. Adaptively and automatically learning the best control parameters in a general setting is interesting and requires further research.

Fourth, we assume that a protected server will send throttle requests to deployment routers by multicast because it is the most natural communication paradigm for our purpose. In practice, we do not need full IP multicast support between routers. For example, using topology information known to routers in an ISP, routers can simply forward a throttle request to upstream routers after incrementing a request hop count by one. Then routers install the throttle when the hop count parameter indicates that they are in the deployment set. In this paper, we do not address the full implementation details of such multicast support.

Fifth, our study assumes that router throttling is supported in a specified set of deployment routers. This simplifies the analysis and experiments. If the assumption is not true, then we must be able to identify at least one alternative supporting router on each network path that sees substantial network traffic. This will then add the overhead of control message exchanges between routers to identify supporting routers. Lastly, priority transmission techniques should be investigated to ensure the reliable and timely delivery of throttle messages from source to destination.

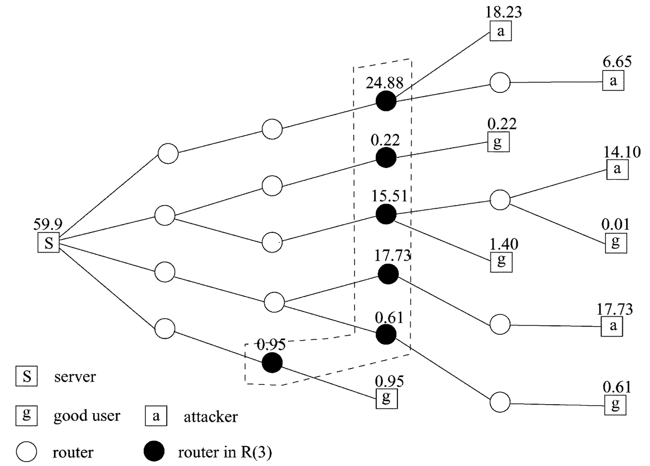


Fig. 1. Network topology illustrating $R(3)$ deployment points of router throttle, and offered traffic rates.

III. System Model

We begin by stating Convention 1 that simplifies our presentation throughout the rest of the paper. Then, we go on to describe our system model.

Convention 1: All traffic rate and server load quantities stated in this paper are in units of kb/s, unless otherwise stated.

We model a network as a connected graph $G = (V, E)$, where V is the set of nodes and E is the set of edges. All leaf nodes are hosts and thus can be a traffic source. Hosts are not trusted. In particular, they may spoof traffic, disobey congestion signals, initiate bogus network requests, etc. An internal node is a router; a router cannot generate traffic, but can forward traffic received from its connected hosts or peer routers. We denote by R the set of internal routing nodes. All routers are assumed to be trusted. The set of hosts, $H = V - R$, is partitioned into the set of ordinary "good" users, H_g, and the set of attackers H_a. E models the network links, which are assumed to be bi-directional. Since our goal is to investigate control against *server* resource overload, each link is assumed to have infinite bandwidth. The assumption can be relaxed if the control algorithm is also deployed to protect routers from overload.

In our control architecture, routers do not exchange control information between each other beyond passing on throttle requests (unlike, for example, traditional routing). This greatly simplifies the runtime overhead of our solution. Rather, the target server makes all control decisions and then instructs the deployment routers to implement the decisions accordingly.

In our study, we designate a leaf node in V as the target server S. A good user sends packets to S at some rate chosen from the range $[0, r_g]$. An attacker sends packets to S at some rate chosen from the range $[0, r_a]$. In principle, while r_g can usually be set to a reasonable level according to how users normally access the service at S (and we assume $r_g \ll U_S$), it is hard to prescribe constraints on the choice of r_a. In this work, we target in particular the kind of attack in which r_a is significantly higher than r_g (although we will also examine system performance when such a condition is not true). This is because if every attacker sends at a rate comparable to a good user, then an attacker must recruit or compromise a large number of hosts to launch an attack with sufficient traffic volume.

When S is under attack, it initiates the throttle defense mechanism outlined in Section I. The throttle does not have to be deployed at every router in the network. Instead, the deployment points are parameterized by a positive integer k and are given by $R(k) \subseteq R$. Specifically, $R(k)$ contains all the routers that are either k hops away from S or less than k hops away from S but are directly connected to a host.

Fig. 1 shows an example network topology. In the figure, a square node represents a host, while a round node represents a router. The host on the far left is the target server S. The routers in $R(3)$ are shaded in the figure. Notice that the bottom-most router in $R(3)$ is only two hops away from S, but is included because it is directly connected to a host.

Given our system model, an important research problem is how to achieve *fair* rate allocation of the server capacity among the routers in $R(k)$. To that end, we define the following notion of *level-k max-min fairness*:

Definition 1 (Level-k Max-Min Fairness): A resource control algorithm achieves **level-k max-min fairness** *among the routers $R(k)$, if the allowed forwarding rate of traffic for S at each router is the router's max-min fair share of some rate r satisfying $L_S \leq r \leq U_S$.*

IV. Throttle Algorithms

A. Baseline Algorithm

We first present a baseline algorithm in which each router throttles traffic for S by forwarding only a fraction f ($0 \leq f \leq 1$) of the traffic. The fraction f is taken to be one when no throttle for S is in effect. In adjusting f according to current server congestion, the algorithm mimics TCP congestion control. Specifically, f is reduced by a multiplicative factor α when S is congested and sends the router a *rate reduction signal*. It is increased by an additive constant β – subject to the condition that $f \leq 1$ – when S has extra capacity and sends the router a *rate increase signal*.

The baseline algorithm that S runs is specified in Fig. 2. It is to be invoked when either (i) the current server load (measured as traffic arrival rate to S) crosses U_S, or (ii) a throttle is in effect

Algorithm baseline_throttle

```
ρ_last := −∞;
while (1)
    monitor traffic arrival rate ρ for time window w;
    if (ρ > U_S) /* throttle not strong enough */
        /* further restrict throttle rate */
        multicast reduction signal to R(k)
    elif (ρ < L_S) /* throttle too strong */
        if (ρ − ρ_last < ε)
          remove rate throttle from R(k);
          break;
        else
          /* try relaxing throttle at the routers */
          multicast increase signal to R(k);
        fi;
    else
        break;
    fi;
end while;
```

Fig. 2. Baseline throttle algorithm specification.

Algorithm fair_throttle

```
ρ_last := −∞;
while (1)
    multicast current rate-r_S throttle to R(k);
    monitor traffic arrival rate ρ for time window w;
    if (ρ > U_S) /* throttle not strong enough */
        /* further restrict throttle rate */
        r_S := r_S/2;
    elif (ρ < L_S) /* throttle too strong */
        if (ρ − ρ_last < ε)
          remove rate throttle from R(k);
          break;
        else
          /* try relaxing throttle by additive step */
          ρ_last := ρ;
          r_S := r_S + δ;
        fi;
    else
        break;
    fi;
end while;
```

Fig. 3. Fair throttle algorithm specification.

TABLE I
TRACE OF THE THROTTLE FRACTION f AND SERVER LOAD FOR THE BASELINE ALGORITHM

Round	f	server load
1	1.00	59.900
2	0.50	29.950
3	0.75	14.975
4	0.70	17.970
5	0.65	20.965

and the current server load drops below L_S. In case (i), S multicasts a rate reduction signal to $R(k)$; in case (ii), it multicasts a rate increase signal. The algorithm can take multiple rounds until a server load within $[L_S, U_S]$ is achieved. Also, if the server load is below L_S, and the next rate increase signal raises the server load by an insignificant amount (i.e., by less than ϵ), we remove the throttle. The monitoring window w should be set to be somewhat larger than the maximum round trip time between S and a router in $R(k)$.

In the example network shown in Fig. 1, let the number above each host (except S) denote the current rate at which the host sends traffic to S. The number above each router denotes the offered rate of traffic at the router, destined for S. Also, let $L_S = 18$, $U_S = 22$, $\alpha = 1/2$, and $\beta = 0.05$. Initially, the total offered load to S exceeds U_S, and hence the baseline throttle algorithm is invoked at S. A rate reduction signal causes each router to drop half of the traffic for S, resulting in a server load of 29.95, still higher than U_S. The next rate reduction signal causes the server load to drop below L_S, at 14.975 and a rate increase signal to be sent, raising the server load to 17.97. Finally, another rate increase signal raises the server to 20.965, which is within $[L_S, U_S]$.

Table I shows how f and the server load change at each round of the algorithm. When the algorithm terminates, the forwarding rates at the deployment routers (from top to bottom of the figure) are 8.708, 0.077, 5.4285, 6.2055, 0.2135 and 0.3325, respectively. The algorithm achieves a server load within the target range of [18, 22]. However, it does *not* achieve level-k max-min fairness, since some router is given a higher rate than another router, even though the latter has unmet demands.

TABLE II
TRACE OF THROTTLE RATE AND ACHIEVED SERVER LOAD FOR THE FAIR ALGORITHM

Round	r_S	server load
1	10	31.78
2	5	16.78
3	6	19.78

B. Fair Throttle Algorithm

The baseline algorithm is not fair because it penalizes all routers equally, irrespective of whether they are greedy or well behaving. We now present a fair throttle algorithm that installs at each router in $R(k)$, a *uniform* leaky bucket rate (i.e., the throttle rate) at which the router can forward traffic for S. Fig. 3 specifies the algorithm by which S determines the throttle rate to be installed. In the specification, r_S is the current throttle rate to be used by S. It is initialized to $(L_S + U_S)/f(k)$, where $f(K)$ is either some small constant, say 2, or an estimate of the number of throttle points typically needed in $R(k)$. We use a constant additive step, δ, to ramp up r_S if a throttle is in effect and the current server load is below L_S.

The fair throttle algorithm is to be invoked as with the baseline algorithm. Each time it is called, it multicasts a rate-r_S throttle to $R(k)$. This will cause a router in $R(k)$ to regulate traffic destined for S to a leaky bucket with rate r_S. The algorithm may then continue in the while loop that iteratively adjusts r_S to an appropriate value. Notice that the additive increase/multiplicative decrease iterative process aims to keep the server load in $[L_S, U_S]$ whenever a throttle is in effect. The termination conditions and choice of w in the fair algorithm are the same as in the baseline algorithm.

We apply the fair throttle algorithm to the previous example scenario in Fig. 1. We initialize r_S to $(L_S + U_S)/4 = 10$, and use an additive step of one. Table II shows how r_S and the aggregate server load evolve. When the algorithm is first invoked with throttle rate 10, the aggregate load at S drops to 31.78. Since the server load still exceeds U_S, the throttle rate is halved to 5, and the server load drops below L_S, to 16.78. As a result, the throttle rate is increased to 6, and the server load becomes 19.78. Since 19.78 is within the target range [18, 22], the throttle

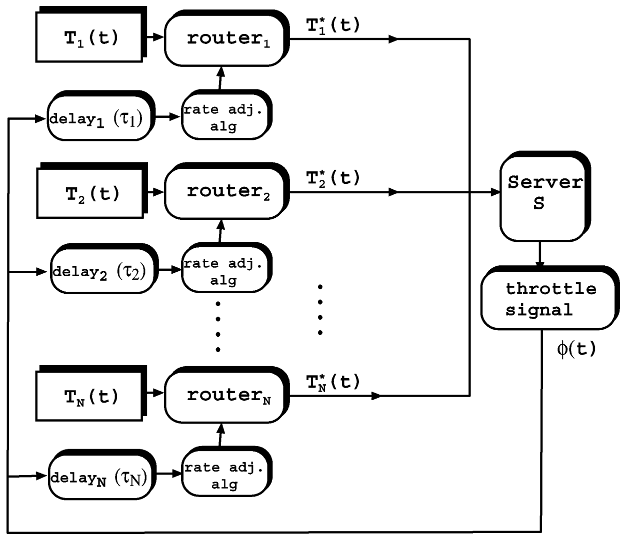


Fig. 4. High-level description of mathematical model for router throttling.

algorithm terminates. When that happens, the forwarding rates of traffic for S at the deployment routers (from top to bottom in the figure) are 6, 0.22, 6, 6, 0.61, and 0.95, respectively. This is the max-min fair allocation of a rate of 19.78 among the deployment routers, showing that level-k max-min fairness is achieved (in the sense of Definition 1).

V. General Mathematical Model

Router throttling is a feedback control strategy. To better understand its stability and convergence behavior, we formulate its control-theoretic model. Using the model, we explore how different system parameters, including feedback delays, the hysteresis control limits $[U_S, L_S]$, and the number and heterogeneity of traffic sources, can impact system performance. We point out that our mathematical model can also provide a general framework for studying various multi-source flow control problems.

Fig. 4 gives a high-level description of our mathematical model for router throttling. We model each deployment router as a source of traffic for S, where S is the server to be protected. Let there be N sources and $T_i(t)$ be the instantaneous *offered* traffic rate from router i has for S at time t. Given a throttle algorithm and a *throttle signal* $\phi(t)$ from S, router i forward traffic for S at an instantaneous rate $T_i^*(t)$. The instantaneous *forwarding* rate $T_i^*(t)$ is a function of the offered traffic rate, $T_i(t)$, and a throttle rate $r_i(t)$ computed by a *rate adjustment module* deployed at router i, according to the throttle algorithm used.

Given $T_i^*(t)$ from each deployment router in $R(k)$, S receives an aggregate traffic rate of $\sum_{i=1}^{N} T_i^*(t)$. Based on the aggregate rate, S computes and sends the throttle signal $\phi(t)$ to all the routers in $R(k)$. Notice that the throttle signal may arrive at different routers at *different* times. We model *heterogeneous delays* from S to different routers in $R(k)$. Specifically, we let $\tau_i \geq 0$ denote the network delay from S to router i. We use a set of coupled differential equations to model the dynamics of how the throttle signal $\phi(t)$, the throttle rate $r_i(t)$, and the forwarding traffic rates $T_i^*(t)$, for $i = 1, \ldots, N$, change over time.

In general, the server S generates a throttle signal $\phi(t)$ as a function of the aggregate traffic workload and the hysteresis control limits $[L_S, U_S]$. The throttle signal generation is:

$$\phi(t) = \begin{cases} -1 & \text{if } \sum_{i=1}^{N} T_i^*(t) \geq U_S \\ 1 & \text{if } \sum_{i=1}^{N} T_i^*(t) \leq L_S \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

In other words, a throttle signal of -1 indicates that the aggregate received traffic rate at S is above U_S and a signal of 1 indicates that the aggregate received traffic rate is below L_S. Note that when the aggregate traffic rate is within $[L_S, U_S]$, the throttle signal will be off (i.e., $\phi(t) = 0$).

A. Mathematical Model for the Fair Throttle Algorithm

Let us consider the fair throttle algorithm. (Because of space constraint, we do not present the analysis of the baseline algorithm in this paper. The interested reader is referred to our technical report [11].) In this case, the server generates a throttle signal $\phi(t)$ as the throttle rate $r_S(t)$, which is a function of the aggregate server workload, the hysteresis control limits L_S and U_S, and the additive step size $\delta > 0$. The differential equation expressing the change in the throttle rate is

$$\frac{dr_S(t)}{dt} = \delta \mathbf{1}_{(\phi(t-\tau_i)==1)} - \frac{r_S(t)}{2} \mathbf{1}_{(\phi(t-\tau_i)==-1)}.$$

Essentially, when the server discovers that the aggregate traffic is below L_S, it will increase the throttle rate $r_S(t)$ by δ. Otherwise, if the aggregate traffic is above U_S, it will reduce the throttle rate $r_S(t)$ by half. The objective is to achieve an aggregate server load within $[L_S, U_S]$.

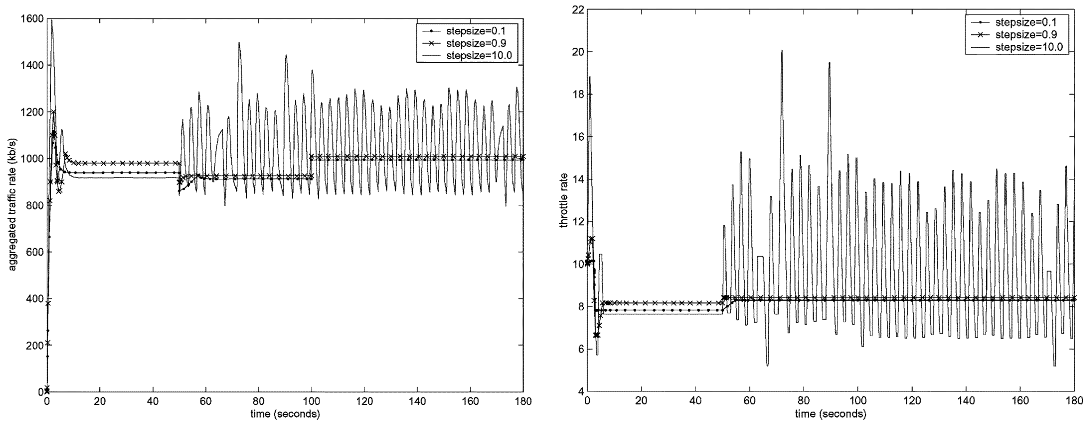
Upon receiving the throttle rate $r_S(t-\tau_i)$, router i adjusts its forwarding traffic rate, $T_i^*(t)$, to S. The differential equation expressing the change in $T_i^*(t)$ is

$$\frac{dT_i^*(t)}{dt} = \min\{r_S(t-\tau_i),\ T_i(t)\} - T_i^*(t)$$

for $i = 1, \ldots, N$ and $T_i^*(0) = 0$. Note that the rate of change of the forwarding traffic rate $T_i^*(t)$ is a function of the throttle rate $r_S(t-\tau_i)$ and the offered traffic rate $T_i(t)$. If the throttle rate $r_S(t-\tau_i)$ is larger than the offered traffic rate, then there is no need to throttle and the change is simply $T_i(t) - T_i^*(t)$. On the other hand, if $r_S(t-\tau_i)$ is smaller than $T_i(t)$, then we throttle and the change in the forwarding traffic rate is $r_S(t-\tau_i) - T_i^*(t)$.

Theorem 1: Assume that the server S is overloaded (i.e., the aggregate received traffic rate is above U_S) at time τ_0, the throttle rate by server S is

$$r_S(t) = C_1 e^{-t/2} \qquad \text{for } t \geq \tau_0 \tag{2}$$



(a) Aggregate workload at server S (b) Throttle rate $r_S(t)$

Fig. 5. System performance for $U_S = 1100$, $L_S = 900$, and various δ step sizes.

where C_1 is a constant equal to $e^{(1/2)\tau_0} r_S(\tau_0)$ and $r_S(\tau_0)$ is the initial value of the throttle rate at time τ_0. The forwarding traffic rate at router i can be closely approximated by

$$T_i^*(t) \approx e^{-t}\left[e^{\tau_0}T_i^*(\tau_0) - \frac{2\alpha C_i}{T_i(t)}\sqrt{C_i^2 + T_i^2(t)e^{\tau_0}} + \frac{2\alpha C_i}{T_i(t)}\sqrt{C_i^2 + T_i^2(t)e^{t}}\right]. \quad (3)$$

Proof: Please refer to [11]. ■

Theorem 2: Assume that the server S is underloaded (i.e., the aggregate received traffic rate is below L_S) at time τ_0, the throttle rate by server S is

$$r_S(t) = \delta t + C_2 \qquad \text{for } t \geq \tau_0 \quad (4)$$

where C_2 is a constant equal to $-\delta\tau_0$. The forwarding traffic rate at router i can be closely approximated by

$$T_i^*(t) \approx \left[T_i^*(\tau_0)e^{\tau_0} - \alpha T_i(t)e^{\tau_0} + \alpha T_i(t) \times \frac{e^{[1-(\delta/T_i(t))]\tau_0}e^{-(C_i/T_i(t))}}{\left(1 - \frac{\delta}{T_i(t)}\right)}\right]e^{-t} + \alpha T_i(t)\left[1 - \frac{e^{-(\delta t + C_i)/T_i(t)}}{\left(1 - \frac{\delta}{T_i(t)}\right)}\right] \quad \text{for } t \geq \tau_0. \quad (5)$$

Proof: Please refer to [11]. ■

B. Mathematical Analysis

We now study the *stability* and *convergence* properties of router throttling. Since the basline algorithm cannot attain the max-min fairness property, we only present results for the fair throttle algorithm. In our presentation, all time units are in seconds, except otherwise stated. In the experiments, we consider 100 *heterogeneous* sources. The first eighty are constant sources wherein $T_i(t) = 30$ for $i = 1, \ldots, 80$. In each experiment, ten of these constant sources are switched off at $t = 50$ and are activated again at $t = 100$. The network delay between S and each of the constant sources is 100 ms. The next ten sources are sinusoidal sources wherein $T_i(t) = 10\sin(0.4t) + 30$ for $i = 81, \ldots, 90$. The network delay for each of these sinusoidal sources is 50 ms. The last ten sources are square-pulse sources wherein

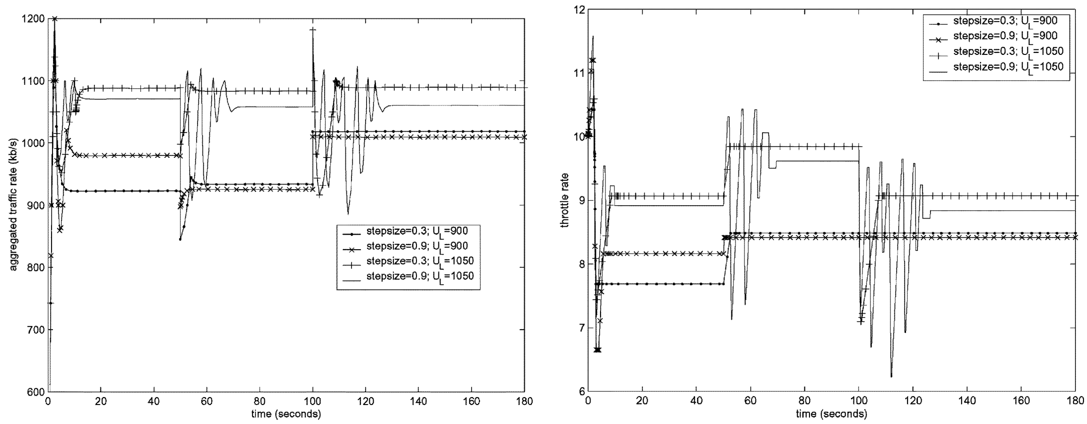
$$T_i(t) = \begin{cases} 50 & \text{for } 20n \leq t < 10(2n+1) \\ 10 & \text{for } 10(2n+1) \leq t < 20(n+1). \end{cases}$$

for $i = 91, \ldots, 100$ and $n \in \{0, 1, 2, \ldots\}$. The network delay for each of these square-pulse sources is 50 ms.

Experiment 1: Handling of heterogeneous sources and system stability. Fig. 5 illustrates the results for the first experiment where $L_S = 900$ and $U_S = 1100$. We consider three different step sizes, namely $\delta = 0.1, 0.9, 10.0$. We make two important observations about the results: 1) The proposed fair algorithm is effective in keeping the server load within the target limits, under *heterogeneous sources* and *heterogeneous network delays*, and 2) the additive step size δ can affect system stability. As shown, system performance is not stable for the large step size of $\delta = 10$. Hence, a small step size relative to $U_S - L_S$ is needed for the system to operate in a stable region.

Experiment 2: Determination of step size δ for a stable system. Fig. 6 illustrates the results of our second experiment where $U_S = 1100$ and L_S can be 900 or 1050. We observe that when $U_S - L_S$ is large, the system is stable with $\delta < 1$, and the achieved server workload at convergence is slightly above 1000. On the other hand, when S advertises a smaller target load region, with $L_S = 1050$ and $U_S = 1100$, we need a smaller step size (e.g, $\delta \leq 0.3$) to have stable performance, and the achieved server workload at convergence is closer to U_S. After experimenting with a large number of different step sizes and many different system configurations, we recommend a small step size of δ (e.g., < 0.5) for system stability.

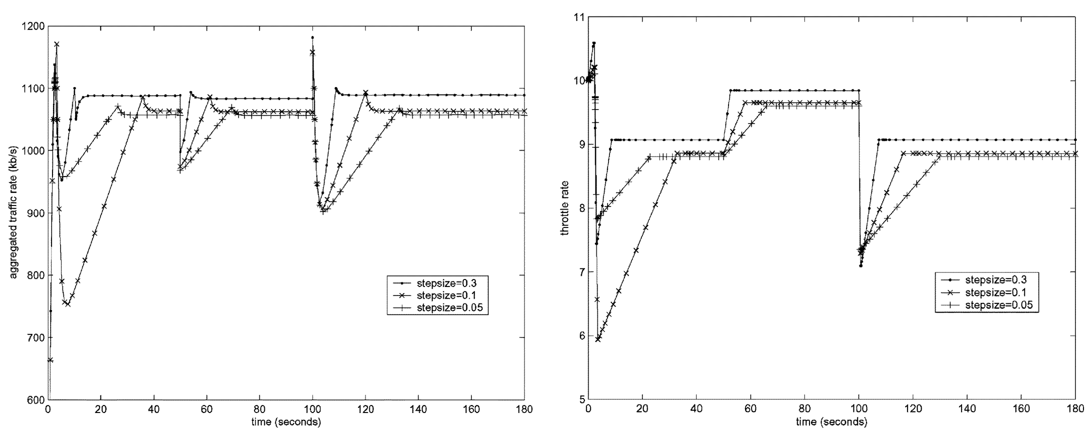
Experiment 3: Effect of δ on the convergence rate. Fig. 7 illustrates the results of our third experiment in which we consider how δ can affect the convergence speed. In the experiment, $L_S = 1050$ and $U_S = 1100$. We experiment with three different step sizes, namely $\delta = 0.3,\ 0.1,\ 0.05$. Although the system is stable for all the three step sizes, we observe that if a step size is too small, it takes *longer* for the system to converge. For example, when ten constant sources are activated at $t = 100$, the system converges around $t = 110$ for $\delta = 0.3$. On the other hand, if we use $\delta = 0.05$, the system



(a) Aggregate workload at server S

(b) Throttle rate $r_S(t)$

Fig. 6. System performance for $U_S = 1100$ and $L_S = 900$ or 1050, and various δ step sizes.



(a) Aggregate workload at server S

(b) Throttle rate $r_S(t)$

Fig. 7. System performance for $U_S = 1100$ and $L_S = 1050$, and various δ step sizes.

converges around $t = 137$. Another important point is that if δ is smaller, the achieved server workload at convergence is also smaller. Therefore, in order to have a stable system *and, at the same time, achieve a high server workload*, we recommend δ to be between 0.1 and 0.3.

VI. Packet Network Simulation Results

Our general, high-level control-theoretic results provide basic understanding about algorithm stability and convergence. To further examine system performance, under detailed packet network models (including both unreliable UDP and reliable TCP communication), we conduct experiments using the ns2 simulator. We present results only for the fair throttle algorithm.

A. Performance Metrics

One basic performance measure is how well router throttles installed by S can floor attackers in their attempt to deny good users of the ability to obtain service from S. It is clear that the defense mechanism cannot completely neutralize the effects of malicious traffic – in part because attackers are themselves entitled to a share of U_S in our model. Hence, good users must see a degraded level of performance, but hopefully are much less prone to *aggressive* attack flows than without network protection.

Apart from the basic performance measure, it is necessary to evaluate the deployment costs of the proposed defense mechanism. Therefore, the following are important evaluation criteria that we adopt:

- The percentage of good user traffic that makes it to the server. Since the control algorithm ensures that the server operates under its maximum designed load, the good user requests that arrive should be adequately served.
- The number of routers involved in protecting S. Because throttling clips forwarding rate to some preset ceiling, it is less tolerant to traffic variabilities than best-effort transmissions. For example, normal traffic that occasionally exceeds the ceiling and cannot be absorbed by the token bucket will get clipped, instead of being served by opportunistic resource availabilites. We measure the number of routers at which traffic is actually dropped due to the throttle rate limit.

B. Packet Network Results

To evaluate how the proposed throttle mechanism would perform over a real network, we conducted simulations using a global network topology reconstructed from real traceroute data. The traceroute data set is obtained from the Internet mapping project at AT&T[2]. It contains 709 310 distinct traceroute paths from a single source to 103 402 different destinations widely distributed over the entire Internet. We use the single source as our target server S, and randomly select 5000 traceroute paths from the original data set for use in our simulations. The resulting graph has a total of 135 821 nodes, of which 3879 are hosts. We assume, therefore, that out of all the hosts in the total global network, these 3879 hosts access S, either as an attacker or a good user.

1) Evenly Distributed Aggressive Attackers: In our first set of experiments, we model *aggressive* attackers, whose average individual sending rate is several times higher than that of normal users. Specifically, each good user is chosen to send fixed size UDP packets to S, where the packet interarrival times are Poisson and the average traffic rate is randomly and uniformly drawn from the range [0, 2]. Each attacker is chosen to send traffic at a rate randomly and uniformly drawn from the range $[0, r_a]$, where r_a is either 10 or 20 according to the particular experiment. Furthermore, we select attackers and good users to be evenly distributed in the network topolgy: each host in the network is independently chosen to be an attacker with probability p, and a good user with probability $1 - p$.

Fig. 8(a) compares the performance of our algorithm (labeled "level-k max-min fairness") with that of the pushback max-min fairness approach in [13], for $r_a = 20$ and $p = 0.2$. We show the percentage of remaining good user and attacker traffic that passes the router throttles and arrives at the server. Fig. 8(b) and (c) show the corresponding results when $r_a = 20$ and $p = 0.4$, and $r_a = 10$ and $p = 0.4$, respectively. We plot the average results over ten independent experimental runs, and show the standard deviation as an error bar around the average.

Notice from the figures that generally, level-k max-min fairness gives significantly better protection for good user traffic than pushback max-min fairness. The performance advantage of level-k max-min fairness increases as k increases, until it levels off at k roughly equal to 20. This is because good traffic can aggregate to a significant level near S (the increase rate can be exponential), making it hard to distinguish from the attacker traffic at that location. Since pushback always originates control at S in our experimental setup (pushback is designed to originate at the point under attack, which can be a congested router in general), it can severely punish good traffic. By initiating control further away from S (specifically, about k hops away), level-k max-min fairness achieves better good user protection.

2) Unevenly Distributed Aggressive Attackers: In this set of experiments, each good user traffic rate is chosen randomly and uniformly from the range [0, 2], while each attacker rate is similarly chosen from the range [0, 20]. In each experiment, about 20% of the hosts are chosen to be attackers, and the remaining hosts to be good users.

In these experiments, we select the attackers to have different *concentration* properties. Specifically, we pick five disjoint subtrees from the network topology, labeled in Fig. 9 as 1–5. The five subtrees have properties as shown in Table III. We then define four concentration configurations, 0–3, for the attackers, as

[2]http://cm.bell-labs.com/who/ches/map/dbs/index.html

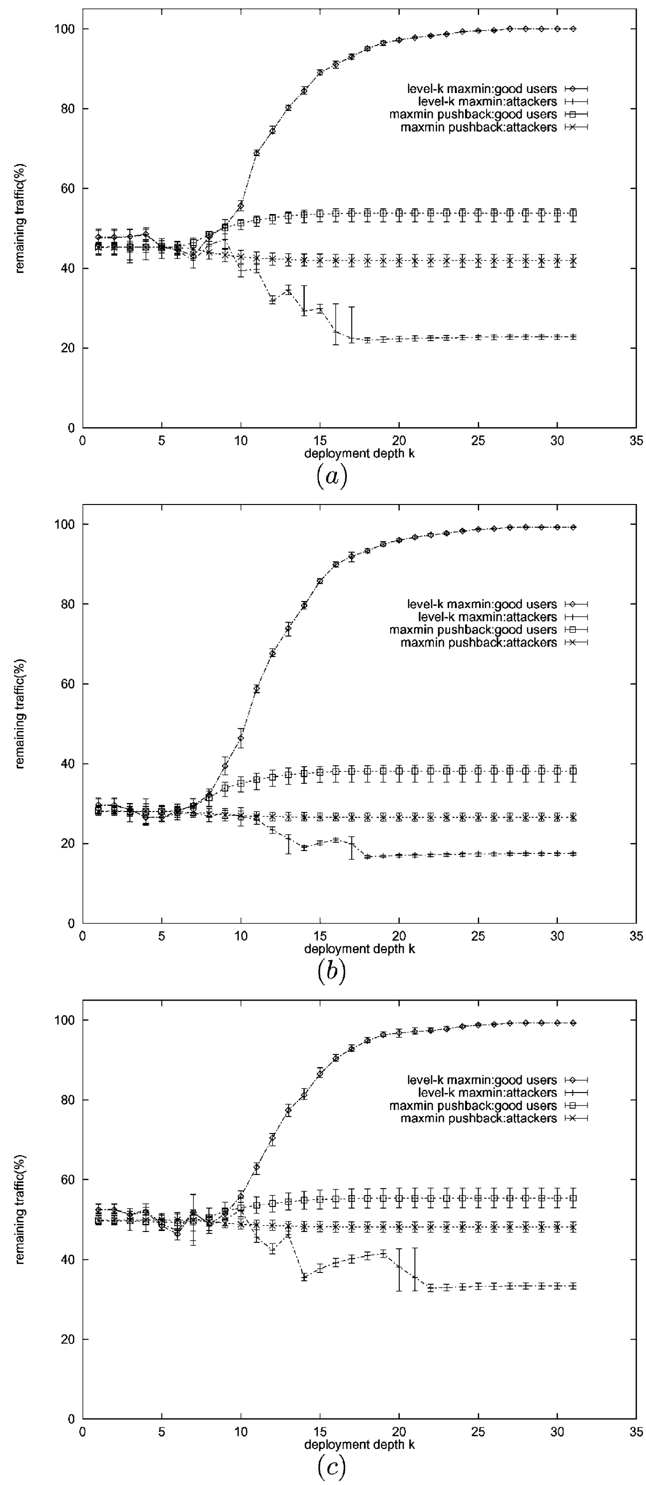


Fig. 8. (a) Protection for good users under 20% evenly distributed aggressive attackers: mean attacker rate 10 times mean good user rate. (b) Protection for good users under 40% evenly distributed aggressive attackers: mean attacker rate 10 times mean good user rate. (c) Protection for good users under 40% evenly distributed moderately aggressive attackers: mean attacker rate 5 times mean good user rate.

shown in Table IV. The intention is for attacker concentration to increase as we go from configurations 0 to 3. (Notice that the roots of subtrees 4 and 5 in configuration 3 share a common parent, and so attacker traffic converges more quickly than the subtrees 1 and 3 in configuration 2.)

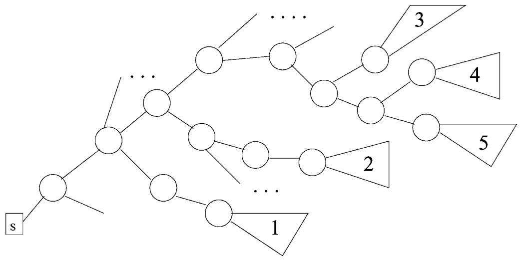


Fig. 9. Subtrees 1–5 used in attacker concentration experiments.

TABLE III
PROPERTIES OF SUBTREES 1–5

Subtree	No. of nodes	No. of hosts	Root's distance from S (hops)
1	1712	459	4
2	1126	476	6
3	1455	448	7
4	1723	490	8
5	1533	422	8

TABLE IV
CONFIGURED CONCENTRATIONS OF ATTACKERS

Configuration	Attackers uniformly chosen from
0	entire graph
1	all the five subtrees
2	subtrees 1 and 3
3	subtrees 4 and 5

Fig. 10(a) shows the percentage of remaining good traffic for the four concentrations, using level-k max-min fairness. Fig. 10(b) shows the corresponding results for pushback max-min fairness. Notice that as k increases, level-k max-min fairness achieves good protection for the good users in all four configurations. For configurations 1–3, however, notice a "dip" in the achieved protection over k values between about 6 to 11. For example, the percentage of remaining good traffic for configuration 3 decreases from $k = 9$ to $k = 11$, and rises again afterwards.

To explain the dip, consider the case when all attackers are contained in *one* subgraph, say G', whose root is m hops away from S. For the traffic seen at $R(k)$, as k *decreases* from m to 1, there will be more and more aggregation of good user traffic *but no further aggregation of attack traffic*. This will cause a larger fraction of good user traffic to be dropped (its volume is more comparable to attack traffic) as throttling is performed with a smaller k, for $k \in [1, m]$. This explains the initial rising curves in Fig. 10(a) before the dip. For k a few hops larger than m, the aggregation situation for both good user and attack traffic is similar to the case of evenly distributed attackers. Hence, we observe increased protection for good user traffic as k increases from $m + c$ onwards, where c is a small constant. This explains the rising curves shortly after the dip. At the point when k *just* increases past the root of G', however, there is progressively less aggregation of attack traffic. This may cause reduced dropping rate for the attack traffic (since its volume at the control points is smaller and more comparable to good user traffic), when compared with control after full attack traffic aggregation has occurred at the root of G'. This explains the dip itself.

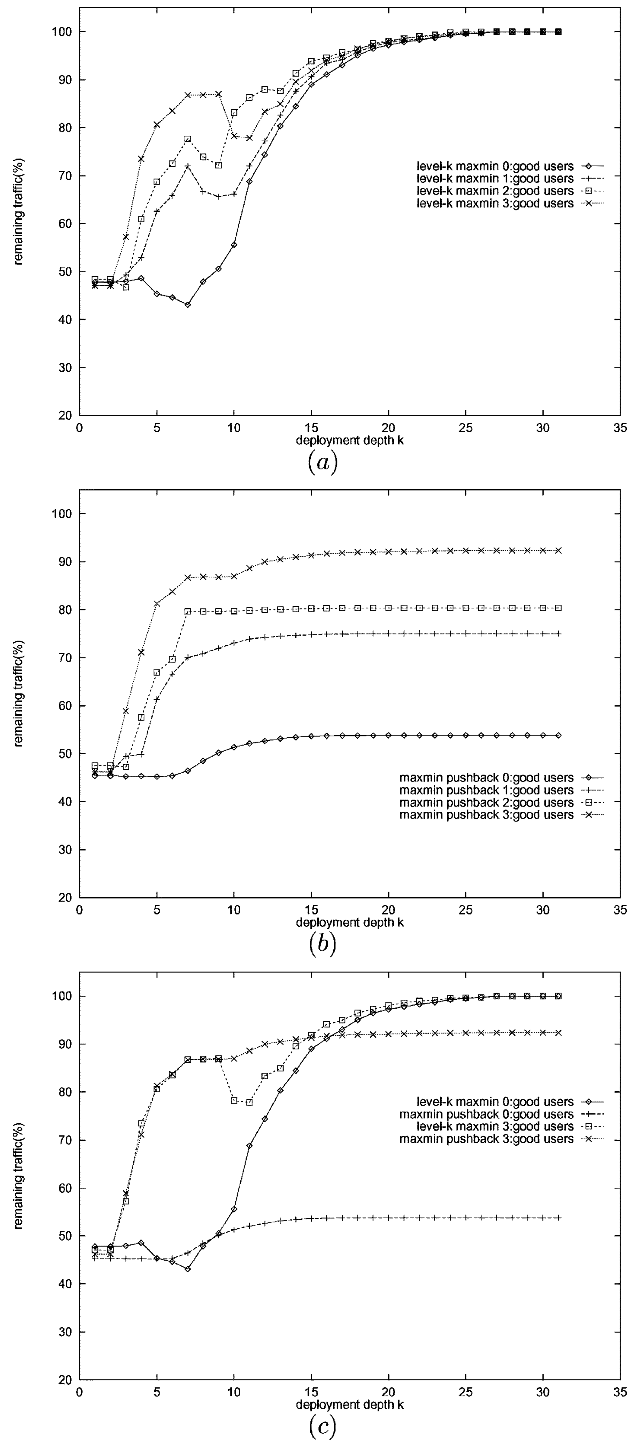


Fig. 10. (a) Protection for good users, under four different attacker concentrations, using level-k max-min fairness. (b) Protection for good users, under four different attacker concentrations, using pushback max-min fairness. (c) Comparions of good-user protection between level-k and pushback max-min fairness – for configurations 0 and 3 only.

Despite the above "anomaly", level-k max-min fairness consistently and signifcantly outperforms pushback max-min fairness for $k > 15$. The performance advantage decreases from 0–3, because pushback max-min fairness becomes more effective as attackers get more concentrated. Fig. 10(c) more clearly compares the two approaches by plotting their results together, for configurations 0 and 3.

3) Evenly Distributed "Meek" Attackers: Router throttling is most effective when attackers are significantly more aggressive than good users. However, should a malicious entity be able to recruit or compromise *many* hosts to launch an attack, then each of these hosts behaving like a normal user can still together bring about denial of service. It is inherently more difficult to defend against such "meek" attackers. Our experimental results (Fig. 11; see also [11]) show that both level-k and max-min fairness may fail to distinguish between the good users and attackers, and punish both classes of hosts equally. When this happens, throttling is mainly useful in regulating the server load to within its operational limits.

4) Deployment Extent: The previous two sets of experiments suggest that, for aggressive attackers, the effectiveness of level-k max-min fairness increases with k. At the same time, however, the cost of deployment may also increase, as the number of routers in $R(k)$ becomes larger.

Fig. 12 plots the percentage of routers involved in throttling as a function of k, for both level-k and pushback max-min fairness. (For the level-k approach, we count both monitoring and throttling routers.) Notice that the two approaches basically require a comparable number of deployment points, although for k equal to 4–9, pushback max-min fairness is somewhat more efficient, and for larger k, level-k max-min fairness is somewhat more efficient. Also, the percentage of deployment points levels off as k rises above 20 for both approaches. This is because as k increases, a throttling node will likely see a progressively smaller rate of traffic destined for S. If the rate is small enough, both algorithms avoid the actual use of a throttle.

5) Web Server Performance: To evaluate the impact of throttling on real user applications, we simulate the performance of a web server under DDoS attack. The simulations are performed using ns2, and clients access the web server via HTTP 1.0 over TCP Reno/IP. (TCP is interesting because the achieved throughput by a client also depends on the rate at which acks are returned from the server to the client.) The simulated network is a subset of the AT&T traceroute topology described above. It consists of 85 hosts, of which 20% (i.e., 17 out of 85) are chosen as attackers. The maximum and average numbers of hops between a client and the server is 30 and 15, respectively.

Attackers generate UDP traffic destined for the server, at a constant rate of 6000 bits/s. Web clients make requests for documents to the server, where the document sizes and times between requests are probabilistically generated according to collected empirical distributions.[3] If a request arrives at the server successfully, the server will return the requested document after a random processing time, also chosen according to collected empirical distributions.

We model the web server to have $L_S = 8\,\mathrm{kbytes/s}$ and $U_S = 10\,\mathrm{kbytes/s}$. We report two experiments with $k = 10$ and $k = 9$, respectively. To compare web server performance with and without throttling, we plot the rates of client requests that are *successfully processed* by the server in both cases, over time. The aggregate rate at which the clients originally make requests is also shown for baseline comparison. Each experiment runs

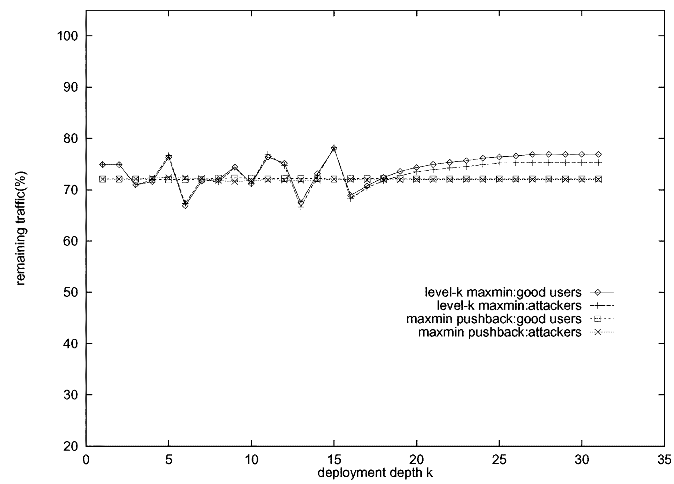


Fig. 11. Protection for good user traffic under evenly-distributed "meek" attackers, for both level-k and pushback max-min fairness.

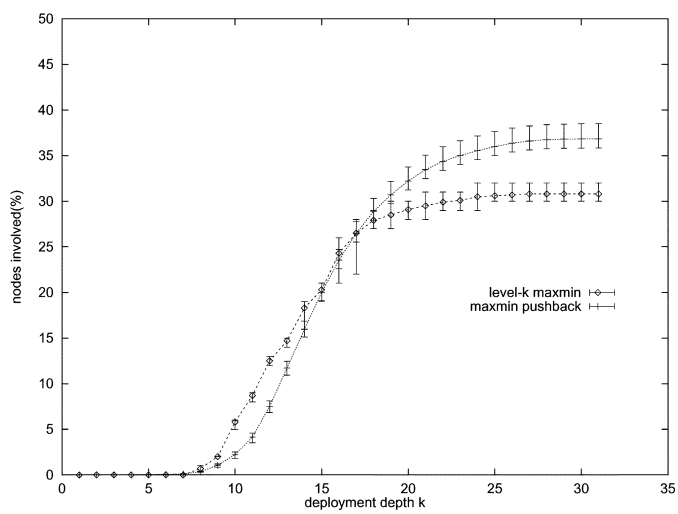


Fig. 12. Number of participating routers for level-k and pushback max-min fairness, as a function of the deployment depth.

for 100 seconds of simulated time, and an attack starts at time 10 seconds.

Fig. 13(a) shows the results for $k = 10$. Notice that with throttling, the rate of client requests that are successfully processed is *much closer to the original client request rate*, than without throttling (the averages are 3.8, 2.5 and 0.9 kbytes/s, respectively). Fig. 13(b) shows the corresponding results for $k = 9$, and supports the same conclusions. Fig. 13(c) shows the web client, attacker, and total traffic arrival rate at the server, for $k = 10$. Notice that our throttle negotiation algorithm is effective in keeping the actual server load between L_S and U_S.

VII. System Implementation

We have an implementation of router throttling on the CROSS/Linux software-programmable router [9]. CROSS/Linux allows a pipeline of processing elements to be flexibly configured for flows of network packets. Each element is implemented in C++ as a Linux loadable kernel module, and can be loaded and dynamically linked into a running kernel. An element initially not present at a router can also

[3]Please see http://http.cs.berkeley.edu/ tomh/wwwtraffic.html for further details.

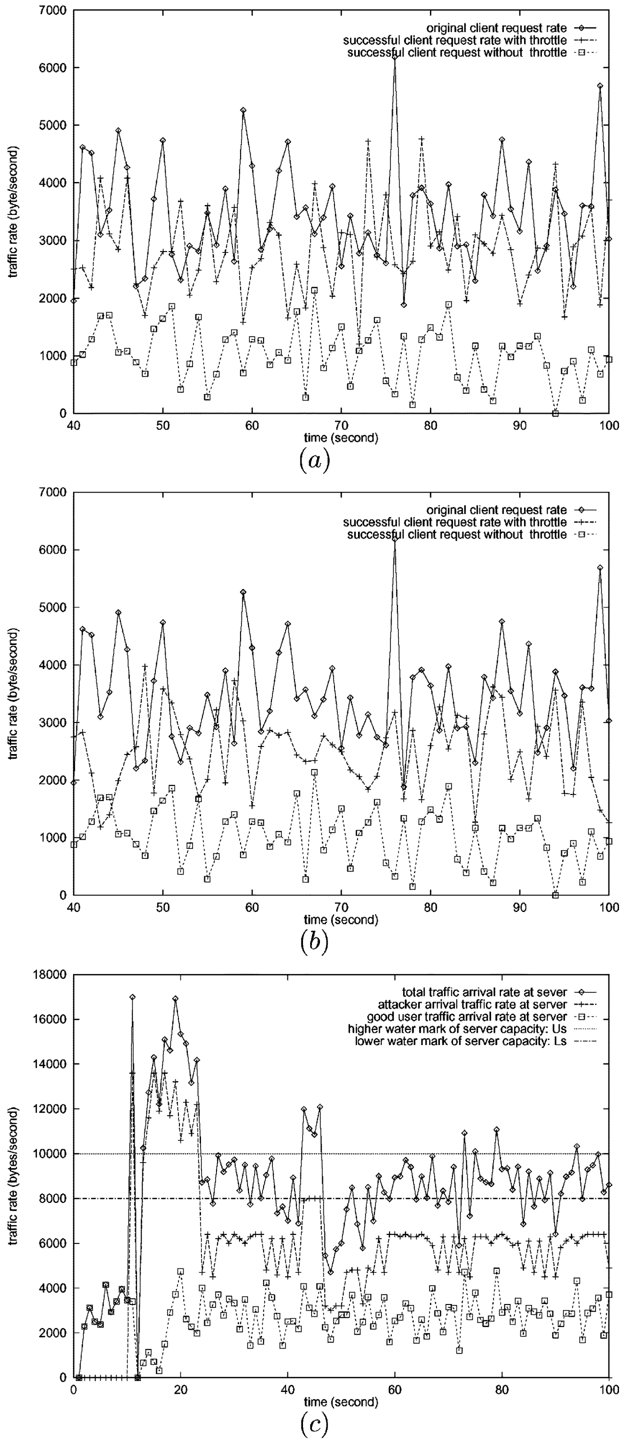


Fig. 13. (a) Plot of (i) original client request rate, (ii) rate of successfully processed client requests with level-10 router throttling, and (iii) rate of successfully processed client requests without throttling, over time. (b) Plot of (i) original client request rate, (ii) rate of successfully processed client requests with level-9 router throttling, and (iii) rate of successfully processed client requests without throttling, over time. (c) Plot of total, attacker, and web client traffic arrival rates at server, over time, for level-10 throttling.

be fetched on demand from a remote code repository, through a modified version of the anetd daemon from DARPA's active network project.

In our implementation, a server, say S, requests throttling at a CROSS/Linux router by sending it an IP control packet with the *router alert* option being set. The control packet specifies the IP address of S, and the throttle leaky bucket size and token rate. On receiving such a packet, CROSS/Linux checks if the throttle element is already available at the local node. If not, it uses anetd to fetch the throttle code from a designated code server, and links the code dynamically into the kernel, without disrupting existing services. When the throttle element has been linked to the kernel, it is configured into the processing pipeline of packets destined for S – just before the IP forwarding path's send onto the outgoing network interface. The element limits the long-term forwarding rate of packets for S to the token rate, and the maximum burst size to the leaky bucket size. Any excess packets are dropped in the implementation.

A. Experimental Results

To measure the memory overhead of router throttle, we first load the CROSS/Linux router and the throttle modules into the kernel. Then, using the /proc file system, we note the amount of memory allocated as 540 kbytes. We then install up to 1000 throttles one by one, observing the increase in memory allocated after each throttle installed. Fig. 14 plots the average memory allocated, as a function of the number of throttles installed, over several experiments. The results show that the memory allocated increases largely linearly with the number of throttles, with an average per-throttle memory of about 7.5 bytes.

We break down the delay of throttling into two components: throttle lookup in the packet classifier, and the delay due to the throttle element itself. We found that the delay through the throttle element is about 200 ns, independent of the number of throttles installed. This small and relatively constant delay shows that throttling is not inherently expensive. Throttle lookup depends heavily on the performance of the packet classifier. We currently use a "naive" implementation that does a linear search through all the installed filters. From Fig. 15, notice that the "base" classifier delay (i.e., without any created flows) is about 150 ns. Following that, the delay increases about linearly with the number of throttles installed, reaching about 475 ns for 18 throttles. Notice, however, that throttle lookup on IP destination addresses is not more complicated than IP forwarding table lookup. Hence, leveraging related results in scalable IP lookup (e.g., [19]) will much improve upon the linear increase in delay.

To ascertain how the throttle overhead affects throughput, we measure the maximum achievable forwarding rates of packets through CROSS/Linux, with no throttled flow, to up to 18 flows created for throttling. Fig. 16 shows the average number of 64-byte packets we can forward per second, as a function of the number of throttled flows.

VIII. Related Work

Probabilistic IP marking is advanced by Savage *et al.* [16] to identify attackers originating a denial-of-service attack, in spite of source address spoofing. The analysis in [15] confirms the remark in [16] that their form of IP traceback may not be highly effective for *distributed* DoS attacks. Subsequently, Song and Perrig [17] improve upon the information convergence rate that allows to reconstruct the attack graph (by eliminating false positives when markers can be fragmented across packets), and

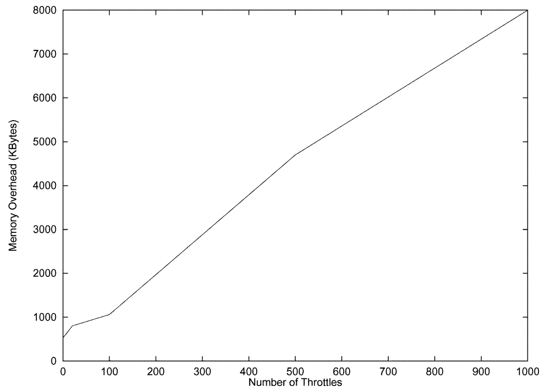


Fig. 14. Router throttle memory overhead, as a function of the number of throttles installed.

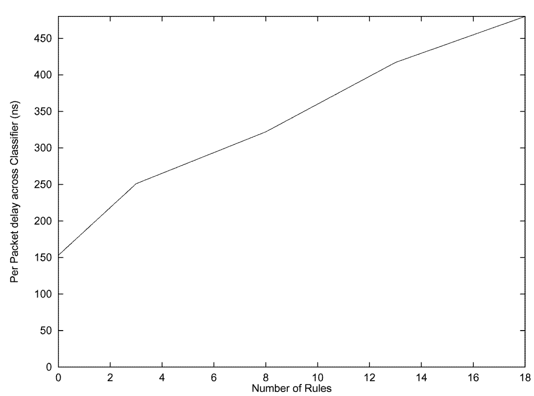


Fig. 15. Delay performance of router throttling, as a function of the number of throttles installed.

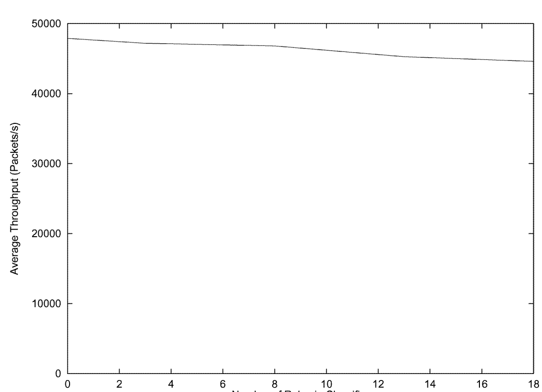


Fig. 16. Throughput performance of router throttling, as a function of the number of throttles installed.

reduces the time overhead in the reconstruction process itself, for DDoS attacks. These algorithms expose the true attackers, which supposedly facilitates defense actions that can then be taken to curtail an attack. However, the required defense mechanisms are external to IP trackeback, which in and of itself offers no active *protection* for a victim server.

To actively defend against attacks, analysis of routing information can enable a router to drop certain packets with spoofed source address, when such a packet arrives from an upstream router inconsistent with the routing information. The approach requires sophisticated and potentially expensive routing table analysis on a per-packet basis. Also, it is not necessary for attackers to spoof addresses in order to launch an attack. The latter observation also limits the effectiveness of ingress filtering approaches [6].

Another approach, adopted by carriers such as AT&T, employs a monitoring infrastructure to detect attacker traffic. Once a network region is determined to be an originator of active attacks, traffic from the region is *blackholed* [1] and thus eliminated from the network. Their approach makes it a binary decision whether a region is an originator of attack traffic or not. In our problem, setting the aggressiveness threshold for the decision is not easy. Our approach assumes that aggressiveness is a matter of degrees, and hence looks at the more fine-grained control problem that regions may have a fraction of the traffic dropped according to how *likely* it is an attack region.

A defense approach most similar to ours is proposed by Mahajan *et al.* [13]. They describe a general framework for identifying and controlling high bandwidth *aggregates* in a network. As an example solution against DDoS attacks, an aggregate can be defined based on destination IP address, as in our proposal. To protect good user traffic from attacker traffic destined for the same victim server, they study recursive *pushback* of max-min fair rate limits starting from the victim server to upstream routers. Similar to level-k max-min fairness, pushback defines a *global* notion of max-min fairness. Unlike level-k max-min fairness, the pushback mechanism always starts the resource sharing decision at the congestion point under attack (e.g., the server), where good user traffic may have aggregated to a large volume and thus can be severely punished (see Section VI-B.I). Such aggregation of normal user traffic has been observed to occur in practice [5].

Architecturally, our control algorithm is more of an end-to-end approach initiated by the server, whereas the proposal in Mahajan *et al.* [13] is more of a hop-by-hop approach in which routers participate more heavily in the control decisions. Hence, our routers have simplified responsibilities, when compared with [13] – they do not need to compute server-centric max-min fair allocations, and are not required to generate and send back *status messages* about current resource state to the server.

The use of authentication mechanisms inside the network will also help defend against DDoS attacks, e.g., IPsec [10]. Recently, Gouda *et al.* [8] propose a framework for providing *hop integrity* in computer networks. Efficient alogrithms for authentication and key exchanges are important research questions in this class of solutions. It is possible to refine the criteria used in throttling for identifying attacker traffic, such as [7], [18].

Lastly, our solution operates at a higher level than packet scheduling techniques like fair queueing (e.g., WFQ [14]). Unlike standard congestion control, our solution is not applied at the point of congestion, but is proactive to avoid *subsequent* aggregation of attack traffc. We also do not require routers to exchange intricate control information (e.g., about resource or congestion states) between each other, greatly simplifying the deployment complexity. Our solution aims to achieve max-min fairness across a potentially large number of flows. Scalable max-min fair allocation in such a situation is studied in [4], where the optimal sharing objective is relaxed to achieve substantial reductions in overhead.

IX. CONCLUSION

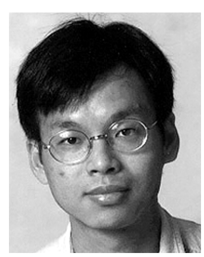
We presented a server-centric approach to protecting a server system under DDoS attacks. The approach limits the rate at which an upstream router can forward packets to the server, so that the server exposes no more than its designed capacity to the global network. In allocating the server capacity among the upstream routers, we studied a notion of level-k max-min fairness, which is policy-free and hence easy to deploy and manage.

Using a control-theoretic mathematical model, we studied stability and convergence issues of router throttling under different system parameters. In addition, we evaluated algorithm effectiveness using a realistic global network topology, and various models for attacker and good user distributions and behaviors. Our results indicate that the proposed approach can offer significant relief to a server that is being flooded with malicious attacker traffic. First, for aggressive attackers, the throttle mechanism can preferentially drop attacker traffic over good user traffic, so that a larger fraction of good user traffic can make it to the server as compared with no network protection. In particular, for the case of aggressive attackers and large k, level-k max-min fairness performs better than recursive pushback of max-min fair rate limits previously proposed in the literature [13]. This is especically the case when attackers are evenly distributed over the network. Second, for both aggressive *and* "meek" attackers, throttling can regulate the experienced server load to below its design limit, so that the server can remain operational during a DDoS attack. Moreover, our implementation results show that throttling has low computation and memory overheads at a deployment router.

Our results indicate that server-centric router throttling is a promising approach to countering DDoS attacks, but several nontrivial challenges remain that prevent its immediate deployment in the Internet. Our focus has been on DDoS attacks in which attackers try to overwhelm a victim server by directing an excessive volume of traffic to the server. Other forms of attacks are possible that do not depend on the sheer volume of attack traffic [12]. However, more sophisticated attack analysis (e.g., intrusion detection) is usually feasible to deal with these other forms of attacks.

REFERENCES

[1] Blackhole Route Server and Tracking Traffic on an IP Network [Online]. Available: http://www.secsup.org/Tracking
[2] TCP SYN Flooding and IP Spoofing Attacks. CERT Advisory CA-96.21. [Online]. Available: http://www.cert.org/
[3] (1998) Smurf IP Denial-of-Service Attacks. CERT Advisory CA-1998-01. [Online]. Available: www.cert.org/advisories/CA-98.01.html
[4] B. Awerbuch and Y. Shavitt, "Converging to approximated max-min flow fairness in logarithmic time," in *Proc. IEEE INFOCOM*, San Francisco, CA, Mar. 1998.
[5] W. Fang and L. Peterson, "Inter-AS traffic patterns and their implications," in *Proc. IEEE Global Internet Symp.*, Rio de Janeiro, Brazil, Dec. 1999.
[6] P. Ferguson and D. Senie, "Network Ingress Filtering: Defeating Denial of Service Attacks Which Employ IP Source Address Spoofing," IETF, RFC 2827, 2000.
[7] A. Garg and A. L. N. Reddy, "Mitigation of DoS attacks through QoS regulation," in *Proc. IEEE IWQoS*, Miami Beach, FL, May 2002.
[8] M. G. Gouda, E. N. Elnozahy, C. T. Huang, and T. M. McGuire, "Hop integrity in computer networks," in *Proc. IEEE ICNP*, Osaka, Japan, Nov. 2000.
[9] S. C. Han, P. Zaroo, D. K. Y. Yau, P. Gopalan, and J. C. S. Lui, "Quality of Service Provisioning for Composable Routing Elements," Purdue Univ., West Lafayette, IN, Tech. Rep., 2002.
[10] S. Kent and R. Atkinson, "Security Architecture for the Internel Protocol," IETF, RFC 2401, 1998.
[11] F. Liang, D. K. Y. Yau, and J. C. S. Lui, "On Defending Against Distributed Denial-of-Service Attacks With Server-Centric Router Throttles," Dept of Computer Sciences, Purdue University, West Lafayette, IN, Tech. Rep. TR-01-008, 2001.
[12] G. de Vivo, M. de Vivo, and G. Isern, "Internet security attacks at the basic levels," *ACM Oper. Syst. Rev.*, vol. 32, Apr. 1998.
[13] R. Mahajan, S. Bellovin, S. Floyd, J. Ioannidis, V. Paxson, and S. Shenker, "Controlling High Bandwidth Aggregates in the Network," ACIRI and AT&T Labs Research, Tech. Rep. , 2001.
[14] A. K. Parekh and R. G. Gallager, "A generalized processor sharing approach to flow control in integrated services networks: The single-node case," *IEEE/ACM Trans. Networking*, vol. 1, pp. 344–357, Jun. 1993.
[15] K. Park and H. Lee, "On the effectiveness of probabilistic packet marking for IP traceback under denial of service attack," in *Proc. IEEE INFOCOM*, Anchorage, AK, 2001.
[16] S. Savage, D. Wetherall, A. Karlin, and T. Anderson, "Practical network support for IP traceback," in *Proc. ACM SIGCOMM*, Stockholm, Sweden, Aug. 2000.
[17] D. Song and A. Perrig, "Advanced and authenticated techniques for IP traceback," in *Proc. IEEE INFOCOM*, Anchorage, AK, 2001.
[18] H. Wang, D. Zhang, and K. G. Shin, "Detecting SYN flooding attacks," in *Proc. IEEE INFOCOM*, New York, NY, Jun. 2002.
[19] D. K. Y. Yau and X. Chen, "Resource management in software-programmable router operating systems," *IEEE J. Select. Areas Commun.*, vol. 19, no. 3, pp. 488–500, Mar. 2001.



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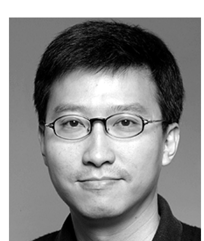

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