CLEF: Limiting the Damage Caused by Large Flows in the Internet Core (Technical Report)

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Abstract. The detection of network flows that send excessive amounts of traffic is of increasing importance to enforce QoS and to counter DDoS attacks. Large-flow detection has been previously explored, but the proposed approaches can be used on high-capacity core routers only at the cost of significantly reduced accuracy, due to their otherwise too high memory and processing overhead. We propose CLEF, a new large-flow detection scheme with low memory requirements, which maintains high accuracy under the strict conditions of high-capacity core routers. We compare our scheme with previous proposals through extensive theoretical analysis, and with an evaluation based on worst-case-scenario attack traffic. We show that CLEF outperforms previously proposed systems in settings with limited memory.

Keywords: Large-flow detection, damage metric, memory and computation efficiency

1 Introduction

Detecting misbehaving large network flows that use more than their allocated resources is not only an important mechanism for Quality of Service (QoS) schemes such as IntServ, but also for DDoS defense mechanisms that allocate bandwidth to network flows. With the recent resurgence of volumetric DDoS attacks, the topics of DDoS defense mechanisms and QoS are gaining importance; thus, the need for efficient in-network accounting is increasing.

Unfortunately, per-flow resource accounting is too expensive to perform in the core of the network, since large-scale Internet core routers have an aggregate capacity of several Terabits per second (Tbps). Instead, to detect misbehaving flows, core routers need to employ highly efficient schemes which do not require

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As in prior literature, the term large flow denotes a flow that sends more than its allocated bandwidth.
them to keep per-flow state. Several approaches for large-flow detection have been proposed in this context; they can be categorized into probabilistic (i.e., relying on random sampling or random binning) and deterministic algorithms. Examples of probabilistic algorithms are Sampled Netflow [11] and Multistage Filters [14,15], while EARDet [42] and Space Saving [29] are examples of deterministic approaches.

However, previously proposed algorithms are able to satisfy the requirements of core router environments only by significantly sacrificing their accuracy. In particular, with the constraints on the amount of high-speed memory on core routers, these algorithms either can only detect flows which exceed their assigned bandwidth by very large amounts, or else they suffer from high false-positive rates. This means that these systems cannot prevent the performance degradation of regular, well-behaved flows, because of large flows that manage to stay “under the radar” of the detection algorithms, or because the detection algorithms themselves erroneously flag and punish the well-behaved flows.

As a numeric example, consider that for EARDet to accurately detect misbehaving flows exceeding a threshold of 1 Mbps on a 100 Gbps link, it would require $10^5$ counters for that link. Maintaining these counters, together with the necessary associated metadata, requires between 1.6 MB and 4MB of state which exceeds typical high-speed memory provisioning for core routers, and would come at a high cost (for comparison, note that only the most high-end commodity CPUs approach the 1–4 MB range with their per-core L1/L2 memory, and the price tag for such processors surpasses USD 4000 [18]).

In this paper we propose a novel randomized algorithm for large flow detection called Recursive Large-Flow Detection (RLFD). RLFD works by considering a set of potential large flows, dividing this set into multiple subsets, and then recursively narrowing down the focus to the most promising subset. This algorithm is highly memory efficient, and is designed to have no false positives. To achieve these properties, RLFD sacrifices some detection speed, in particular for the case of multiple concurrent large flows. We improve on these limitations by combining RLFD with the deterministic EARDet, proposing a hybrid scheme called CLEF, short for in-Core Limiting of Egregious Flows. We show how this scheme inherits the strengths of both algorithms: the ability to quickly detect very large flows of EARDet (which it can do in a memory efficient way), and the ability to detect low-rate large flows with minimal memory footprint of RLFD.

To have a significant comparison with related work, we define a damage metric which estimates the impact of failed, delayed, and incorrect detection on well-behaved flows. We use this metric to compare RLFD and CLEF with previous proposals, which we do both on a theoretical level and by evaluating the amount of damage caused by (worst-case) attacks. Our evaluation shows that CLEF performs better than previous work under realistic memory constraints,

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6 The IP metadata consists of source and destination addresses, protocol number, and ports. Thus, it requires about 16 bytes and 40 bytes per counter for IPv4 and IPv6, respectively.
both in terms of our damage metric and in terms of false negatives and false positives.

To summarize, this paper’s main contributions are the following: a novel, randomized algorithm, RLFD, that provides eventual detection of persistently large flows with very little memory cost; a hybrid detection scheme, CLEF, which offers excellent large-flow detection properties with low resource requirements; the analysis of worst-case attacks against the proposed large-flow detectors, using a damage metric that allows a realistic comparison with the related work.

2 Problem Definition

This paper aims to design an efficient large-flow detection algorithm that minimizes the damage caused by misbehaving flows. This section introduces the challenges of large-flow detection and defines a damage metric to compare different large-flow detectors. We then define an adversary model in which the adversary adapts its behavior to the detection algorithm in use.

2.1 Large-Flow Detection

A flow is a collection of related traffic; for example, Internet flows are commonly characterized by a 5-tuple (source / destination IP / port, transport protocol). A large flow is one that exceeds a flow specification during a period of length $t$. A flow specification can be defined using a leaky bucket descriptor $TH(t) = \gamma t + \beta$, where $\gamma > 0$ and $\beta > 0$ are the maximum legitimate rate and burstiness allowance, respectively. Flow specifications can be enforced in two ways: arbitrary-window, in which the flow specification is enforced over every possible starting time, or landmark-window, in which the flow specification is enforced over a limited set of starting times.

Detecting every large flow exactly when it exceeds the flow specification, and doing so with no false positives requires per-flow state (this can be shown by the pigeonhole principle [38]), which is expensive on core routers. In this paper, we develop and evaluate schemes that trade timely detection for space efficiency.

As in prior work in flow monitoring, we assume each flow has a unique and unforgeable flow ID, e.g., using source authentication techniques such as accountable IPs [1], ICING [32], IPA [24], OPT [20], or with Passport [25]. Such techniques can be deployed in the current Internet or in a future Internet architecture, e.g., Nebula [2], SCION [44], or XIA [17].

Large-flow detection by core routers. In this work, we aim to design a large-flow detection algorithm that is viable to run on Internet core routers. The algorithm needs to limit damage caused by large flows even when handling worst-case background traffic. Such an algorithm must satisfy these three requirements:

– Line rate: An in-core large-flow detection algorithm must operate at the line rate of core routers, which can process several hundreds of gigabits of traffic per second.
– **Low memory:** Large-flow detection algorithms will typically access one or more memory locations for each traversing packet; such memory must be high-speed (such as on-chip L1 cache). Additionally, such memory is expensive and usually limited in size, and existing large-flow detectors are inadequate to operate in high-bandwidth, low-memory environments. An in-core large-flow detection algorithm should thus be highly space-efficient. Though perfect detection requires counters equal to the maximum number of simultaneous large flows (by the pigeonhole principle [38]), our goal is to perform effective detection with much fewer counters.

– **Low damage:** With the performance constraints of the previous two points, the large-flow detection algorithm should also minimize the damage to honest flows, which can be caused either by the excessive bandwidth usage by large flows, or by the erroneous classification of legitimate flows as large flows (false positives). Section 2.2 introduces our damage metric, which takes both these aspects into account.

### 2.2 Damage Metric

We consider misbehaving large flows to be a problem mainly in that they have an adverse impact on honest flows. To measure the performance of large flow detection algorithms we therefore adopt a simple and effective damage metric which captures the packet loss suffered by honest flows. This metric considers both (1) the direct impact of excessive bandwidth usage by large flows, and (2) the potential adverse effect of the detection algorithm itself, which may be prone to false positives resulting in the blacklisting of honest flows. Specifically, we define our damage metric as $D = D_{over} + D_{fp}$, where $D_{over}$ (overuse damage) is the total amount of traffic by which all large flows exceed the flow specification, and $D_{fp}$ (false positive damage) is the amount of legitimate traffic incorrectly blocked by the detection algorithm. The definition of the overuse damage assumes a link at full capacity, so when this is not the case the damage metric represents an overapproximation of the actual traffic lost suffered by honest flows. We note that the metrics commonly used by previous work, i.e., false positives, false negatives, and detection delay, are all reflected by our metric.

### 2.3 Attacker Model

In our attacker model, we consider an adversary that aims to maximize damage. Our attacker responds to the detection algorithm and tries to exploit its transient behavior to avoid detection or to cause false detection of legitimate flows.

Like Estan and Varghese’s work [15], we assume that attackers know about the large-flow detection algorithm running in the router and its settings, but have no knowledge of secret seeds used to generate random variables, such as the detection intervals for landmark-window-based algorithms [12,13,15,16,19,28,30], and random numbers used for packet/flow sampling [15]. This assumption prevents the attacker from performing optimal attacks against randomized algorithms.
We assume the attacker can interleave packets, but is unable to spoof legitimate packets (as discussed in Section 2.1) or create pre-router losses in legitimate flows. Figure 1 shows the network model, where the attacker arbitrarily interleaves attack traffic \( (A) \) between idle intervals of legitimate traffic \( (L) \), and the router processes the interleaved traffic to generate output traffic \( (O) \) and perform large-flow detection. Our model does not limit input traffic, allowing for arbitrary volumes of attack traffic.

In our model, whenever a packet traverses a router, the large-flow detector receives the flow ID (for example, the source and destination IP and port and transport protocol), the packet size, and the timestamp at which the packet arrived.

3 Background and Challenges

In this section we briefly review some existing large flow detection algorithms, and discuss the motivations and challenges of combining multiple algorithms into a hybrid scheme.

3.1 Existing Detection Algorithms

We review the three most relevant large-flow detection algorithms, summarized in Table 1. We divide large flows into low-rate large flows and high-rate large flows, depending on the amount by which they exceed the flow specification.

**EARDet.** EARDet [42] guarantees exact and instant detection of all flows exceeding a high-rate threshold \( \gamma_h = \frac{\rho}{m} \), where \( \rho \) is the link capacity and \( m \) is the number of counters. However, EARDet may fail to identify a large flow whose rate stays below \( \gamma_h \).

**Multistage Filters.** Multistage filters [14, 15] consist of multiple parallel stages, each of which is an array of counters. Specifically, arbitrary-window-based Multistage Filter (AMF), as classified by Wu et al. [42], uses leaky buckets as counters. AMF guarantees the absence of false negatives (no-FN) and immediate detection for any flow specification; however, AMF has false positives (FPs), which increase as the link becomes congested (as shown in Appendix B.2).

**Flow Memory.** Flow Memory (FM) [15] refers to per-flow monitoring of select flows. FM is often used in conjunction with another system that specifies which flows to monitor; when a new flow is to be monitored but the flow memory is full, FM evicts an old flow. We follow Estan and Varghese [15]'s random
eviction. If the flow memory is large enough to avoid eviction, it provides exact
detection. In practice, however, Flow Memory is unable to handle a large number
of flows, resulting in frequent flow eviction and potentially high FN. The analysis
in Appendix B.1 shows that FM’s real-world performance depends on the amount
by which a large flow exceeds the flow specification: high-rate flows are more
quickly detected, which improves the chance of detection before eviction.

Table 1: Comparison of three existing detection algorithms. None of them achieve
all desired properties.

| Algorithm   | EARDet | AMF | FM  |
|-------------|--------|-----|-----|
| No-FP       | yes    | no  | yes |
| No-FN       | low-rate: no** | yes | no* |
|             | high-rate: yes | yes | yes*** |
| Instant detection | yes | yes | yes |

* Appendix B.1 and B.2 show that Flow Memory has high FN and AMF has high FP
  for low-rate large flows when memory is limited.
** EARDet cannot provide no-FN when memory is limited.
*** Flow Memory has nearly zero FN when large-flow rate is high.

3.2 Advantages of Hybrid Schemes

As Table 1 shows, none of the detectors we examined can efficiently achieve no-
FN and no-FP across various types of large flows. However, different detectors
exhibit different strengths, so combining them could result in improved perfor-
mance.

One approach is to run detectors sequentially; in this composition, the first
detector monitors all traffic and sends any large flows it detects to a second
detector. However, this approach allows an attacker controlling multiple flows to
rotate overuse among many flows, overusing a flow only for as long as it takes
the first detector to react, then sending at the normal rate so that remaining
detectors remove it from their watch list and re-starting with the attack.

Alternatively, we can run detectors in parallel: the hybrid detects a flow
whenever it is identified by either detector. (Another configuration is that a flow
is only detected if both detectors identify it, but such a configuration would have
a high FN rate compared to the detectors used in this paper.) The hybrid inherits
the FPs of both schemes, but features the minimum detection delay of the two
schemes and has a FN only when both schemes have a FN. The remainder of
this paper considers the parallel approach that identifies a flow whenever it is
detected by either detector.

The EARDet and Flow Memory schemes have no FPs and are able to quickly
detect high-rate flows; because high-rate flows cause damage much more quickly,
rapid detection of high-rate flows is important to achieving low damage. Com-
bining EARDet or Flow Memory with a scheme capable of detecting low-rate
flows as a hybrid detection scheme can retain rapid detection of high-rate flows
while eventually catching (and thus limiting the damage of) low-rate flows. In this paper, we aim to construct such a scheme. Specifically, our scheme will selectively monitor one small set at a time, ensuring that a consistently-overusing flow is eventually detected.

4 RLFD and CLEF Hybrid Schemes

In this section, we present our new large-flow detectors. First, we describe the Recursive Large-Flow Detection (RLFD) algorithm, a novel approach which is designed to use very little memory but provide eventual detection for large flows. We then present the data structures, runtime analysis, and advantages and disadvantages of RLFD. Next, we develop a hybrid detector, CLEF, that addresses the disadvantages of RLFD by combining it with the previously proposed EARDet [42]. CLEF uses EARDet to rapidly detect high-rate flows and RLFD to detect low-rate flows, thus limiting the damage caused by large flows, even with a very limited amount of memory.

4.1 RLFD Algorithm

RLFD is a randomized algorithm designed to perform memory-efficient detection of low-rate large flows; it is designed to scale to a large number of flows, as encountered by an Internet core router. RLFD is designed to limit the damage inflicted by low-rate large flows while using very limited memory. The intuition behind RLFD is to monitor subsets of flows, recursively subdividing the subset deemed most likely to contain a large flow. By dividing subsets in this way, RLFD exponentially reduces memory requirements (it can monitor $m^d$ flows with $O(m + d)$ memory).

The main challenges addressed by RLFD include efficiently mapping flows into recursively divided groups, choosing the correct subdivision to reduce detection delay and FNs, and configuring RLFD to guarantee the absence of FPs.

**Recursive subdivision.** To operate with limited memory, RLFD recursively subdivides monitored flows into $m$ groups, and subdivides only the one group most likely to contain a large flow.

We can depict an RLFD as a virtual counter tree (Figure 2(a)) of depth $d$. Every non-leaf node in this tree has $m$ children, each of which corresponds to a virtual counter. The tree is a full $m$-ary tree of depth $d$, though at any moment, only one node ($m$ counters) is kept in memory; the rest of the tree exists only virtually.

Each flow $f$ is randomly assigned to a path $PATH(f)$ of counters on the virtual tree, as illustrated by the highlighted counters in Figure 2(b). This mapping is determined by hashing a flow ID with a keyed hash function, where the key is randomly generated by each router. Section 4.2 explains how RLFD efficiently implements the virtual tree mapping, but our technique differs in both approach and goal. Chen et al. efficiently manage a sufficient number of counters for per-flow accounting, while RLFD manages an insufficient number of counters to detect consistent overuse.
Since there are \(d\) levels, each leaf node at level \(L_d\) will contain an average of \(n/m^{d-1}\) flows, where \(n\) is the total number of flows on the link. A flow \(f\) is identified as a large flow if it is the only flow associated with its counter at level \(L_d\) and the counter value exceeds a threshold \(TH_{RLFD}\). To reflect the flow specification \(TH(t) = \gamma t + \beta\) from Section 2.1, we set \(TH_{RLFD} = \gamma T_{\ell} + \beta\), where \(T_{\ell}\) is the duration of the period during which detection is performed at the bottom level \(L_d\). Any flow sending more traffic than \(TH_{RLFD}\) during any duration of time \(T_{\ell}\) must violate the large-flow threshold \(TH(t)\), so RLFD has no FPs. We provide more details about how we balance detection rate and the no-FP guarantee in Appendix A.1.

RLFD considers only one node in the virtual counter tree at a time, so it requires only \(m\) counters. To enable exploration of the entire tree, RLFD divides the process into \(d\) periods; in period \(k\), it loads one tree node from level \(L_k\). Though these periods need not be of equal length, in this paper we consider periods of equal length \(T_{\ell}\), which results in a RLFD detection cycle \(T_c = d \cdot T_{\ell}\).

RLFD always chooses the root node to monitor at level \(L_1\); after monitoring at level \(L_k\), RLFD identifies the largest counter \(C_{\text{max}}\) among the \(m\) counters at level \(L_k\), and uses the node corresponding to that counter for level \(L_{k+1}\). Section 5.3 shows that choosing the largest counter detects large flows with high probability.

Figure 2(c) shows an example with \(m = 4\) counters, \(n = 7\) flows, and \(d = 2\) levels. \(f_L\) is a low-rate large flow. In level \(L_1\), the largest counter is the one associated with large flow \(f_L\) and legitimate flows \(f_2\) and \(f_6\). At level \(L_2\), the flow set \(\{f_L, f_2, f_6\}\) is selected and sub-divided. After the second round, \(f_L\) is detected because it violates the counter value threshold \(TH_{RLFD}\).

Algorithm description. As shown in Figure 3(a), the algorithm starts at the top level \(L_1\) so each counter represents a child of the root node. At the beginning of each period, all counters are reset to zero. At the end of each period, the algorithm finds the counter holding the maximum value and moves
to the corresponding node, so each counter in the next period is a child of that node. Once the algorithm has processed level $d$, it repeats from the first level.

Figure 3(b) describes how RLFD processes each incoming packet. When RLFD receives a packet $x$ from flow $f$, $x$ is dropped if $f$ is in the blacklist (a table that stores previously-found large flows). If $f$ is not in the blacklist, RLFD hashes $f$ to the corresponding counters in the virtual counter tree (one counter per level of the tree). If one such counter is currently loaded in memory, its value is increased by the size of the packet $x$. At the bottom level $L_d$, a large flow is identified when there is only one flow in the counter and the counter value exceeds the threshold $TH_{RLFD}$. To increase the probability that a large flow is in a counter by itself, we choose $d \geq \lceil \log m \rceil$ and use Cuckoo hashing [33] at the bottom level to reduce collisions. Once a large flow is identified, it is blacklisted: in our evaluation we calculate the damage $D$ with the assumption that large flows are blocked immediately after having been added to the blacklist.

![Level Change Diagram](attachment:image.png)

(a) Level Change Diagram.

![Packet Processing Diagram](attachment:image.png)

(b) Packet Processing Diagram.

Fig. 3: RLFD Decision Diagrams. “V.C.” stands for virtual counter.

### 4.2 Implementation of Hashing and Counter Checking

Hashing each flow $f$ into a path of virtual counters $PATH(f)$ and checking whether any of these counters are loaded in the memory are two performance-critical operations of RLFD.

For each packet, our implementation only requires three bitwise operations (a hash operation, a bitwise AND operation, and a comparison over 64 bits), thus requiring only $O(1)$ time\(^8\) and $O(1)$ space on a modern 64-bit CPU.

A naive implementation of hashing could introduce unnecessary cost in computation and space. For example, a naive implementation may maintain one hash function per virtual counter array. To check whether an incoming flow needs to be monitored, it would have to check whether the incoming flow is hashed into

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\(^8\) This is not entirely exact, as the length of the hash output has to increase as $O(d \log m)$. However, in any realistic scenario $d \log m$ is small enough to be considered constant.
every maximum-value counter in each level above the current level. However, this would take $O(d)$ time for checking level by level and $O(d)$ space for hash functions, where $d$ is the depth of the virtual counter tree.

\[
H(f) \triangleq \begin{cases} b_0b_1b_2 \ldots b_{s(k-1)} \ldots b_{sk} \ldots b_{sd-2}b_{sd-1} & \text{For } L_1 \\ \text{For } L_4 \\ \text{For } L_{k-1} \end{cases}
\]

\[
M(L_k) \triangleq \begin{bmatrix} 111111 \ldots 111111 & 0000 \ldots 000000 \end{bmatrix}
\]

\[
A(l_{i,k}) \triangleq \begin{cases} \alpha_0\alpha_1\alpha_2 \ldots \alpha_{s(k-2)} \ldots \alpha_{sk(k-1)-1} 00 \ldots 000 & \text{For } L_1 \\ \text{For } L_4 \\ \text{For } L_{k-1} \end{cases}
\]

\[
H(f) \text{ AND } M(L_k) \begin{cases} = A(l_{i,k}) & f's \text{ V.C. is in the loaded counter array } l_{i,k} \\ \neq A(l_{i,k}) & f's \text{ V.C. is not in the loaded counter array } l_{i,k} \end{cases}
\]

Fig. 4: RLFD Counter Hash and In-memory check. $H(f)$ reflects the hash-generated bin number for all levels, $M(L_k)$ reflects a mask that includes the first $k - 1$ levels, and $A(l_{i,k})$ reflects the bins selected in each of the first $k - 1$ levels. Flow $f$ is in the $i, k$ counter array exactly when $H(f) \& M(L_k) = A(l_{i,k})$.

Inspired by how a network router finds the subnet of an IP address, as Figure 4 illustrates, we map a flow to a virtual counter per level based on a single hash value. Specifically, given an incoming flow $f$, we compute $H(f)$, and then do a bitwise AND operation of $H(f)$ and a mask value $M(L_k)$ of the current level $L_k$. We then check whether the result is equal to the hash value $A(l_{i,k})$ of the currently loaded counter array $l_{i,k}$ (the $i$th counter array in the $k$th level). If the $H(f)$ AND $M(L_k) = A(l_{i,k})$, then the virtual counter of $f$ in the level $L_k$ is in the currently loaded counter array $l_{i,k}$.

Assuming RLFD has $d$ levels and $m$ counters in each counter array, we hash a flow ID $f = \text{fid}(x)$ into $H(f)$ with $s \cdot d$ bits, where $s = \log_2 m$. We require the system designer to only choose the base-2 exponential value for $m$, so that the $s$ is an integer.

The bits $[b_{sk} \ldots b_{sk-1}]$ of $H(f)$ are the index of the virtual counter in its counter array in the $k$th level $L_k$. As each counter array is determined by its ancestor counters as Figure 2(b) describes, the bits $b_{sk} : b_{sk(k-1)-1}$ can uniquely determine the counter array in the level $L_k$ for the flow $f$. Thus, to check whether the virtual counters of a flow is in memory, we just need to track the ancestor counters of the currently loaded counter array $l_{i,k}$. We track the ancestor counters by $A(l_{i,k})$, which is also a value of $s \cdot d$ bits. The bits $[a_0 : a_{sk(k-1)-1}]$ record the index of ancestor counters of $l_{i,k}$, and the rest of bits are all 0s. To track $A(l_{i,k})$, we just simply set the bits $[a_{sk(k-1)} : a_{sk-1}]$ as the index of the selected counter at the end of the period of $L_k$. The mask value for the level $L_k$ is also a value of $s \cdot d$ bits, whose first $s(k-1)$ bits are 1s and the rest are 0s.

\[ [b_i : b_j] \text{ denotes a block of bits } \{b_k\}, \ i \leq k \leq j. \]
are 0s. By \( H(\text{fid}(x)) \) AND \( M(L_k) \), we extract the ancestor bits \([b_0 : b_{s(k-1)-1}]\) of the flow \( \text{fid}(x) \), and compare it with the ancestor bits \([a_0 : a_{s(k-1)-1}]\) of the loaded counter array. If they match, then the flow \( \text{fid}(x) \)'s counter is in the memory, and we update the counter with index \([b_{s(k-1)} : b_{sk-1}]\) by the size of the packets of the flow \( \text{fid}(x) \).

For each packet, our implementation above only need three basic operations: a hash operation, an AND operation, and a comparison over \( d \log_2 m \) bits. Although the number of bits used in this implementation depends on \( d \) and \( m \), a 64-bit long integer is enough in most of the cases, thus those operations only take \( O(1) \) CPU cycles in a modern 64-bit CPU.

4.3 RLFD Details and Optimization

We describe some of the details of RLFD and propose additional optimizations to the basic RLFD described in Section 4.1.

**Hash function update.** We update the keyed hash function by choosing a new key at the beginning of every initial level to guarantee that the assignment of flows to counters between different top-to-bottom detection cycles is independent and pseudo-random. For simplicity, in this paper we analyze RLFD assuming the random oracle model. Picking a new key is computationally inexpensive and needs to be performed only once per cycle.

**Blacklist.** When RLFD identifies a large flow, the flow’s ID should be added to the blacklist as quickly as possible. Thus, we implement the blacklist with a small amount of L1 cache backed by permanent storage, e.g., main memory. Because the blacklist write only happens at the bottom-level period and the number of large flows detected in one iteration of the algorithm is at most one, we first write these large flows in the L1 cache and move them from L1 cache to permanent storage at a slower rate. By managing the blacklist in this way, we provide high bandwidth for blacklist writing, defending against attacks that overflow the blacklist.

**Using multiple RLFDs.** If a link handles too much traffic to use a single RLFD, we can use multiple RLFDs in parallel. Each flow is hashed to a specific RLFD so that the load on each detector meets performance requirements. The memory requirements scale linearly in the number of RLFDs required to process the traffic.

4.4 RLFD Runtime Analysis

We analyze the runtime using the same CPU considered in EARDet [42]. An OC-768 (40 Gbps) high-speed link can accommodate 40 million mid-size (1000 bit) packets per second. To operate at the line rate, a modern 3.2 GHz CPU must process each packet within 76 CPU cycles. A modern CPU might contain 32 KB L1 cache, 256 KB L2 cache, and 20 MB L3 cache. It takes 4, 12, and 30 CPU cycles to access L1, L2, and L3 CPU cache, respectively; accessing main memory is as slow as 300 cycles.
If, over a 40-Gbps link, we conservatively pick a large-flow threshold rate \( \gamma = 100 \) kbps, a maximum of 400,000 flows can be supported. An RLFD with 400,000 flows and 128 counters per level only needs \( d = 3 \) levels to get an average of 24.4 flows at the bottom level, causing only a few collisions for the 128 counters at the bottom level which will be handled by the Cuckoo hashing approach. Even if we consider a much larger number of flows, such as 40 million, \( d = 4 \) levels results in around 19.1 flows at the bottom level. In such a 4-level RLFD, a flow’s path through the tree will require only \( 4 \cdot \log_2 128 = 28 \) bits, so a 64-bit integer is large enough for the hash value. In practice, the threshold rate is higher than 100 kbps, and the number of flows is likely to be under 40 million.

**Computational complexity.** Based on the implementation and optimizations in Sections 4.2 and 4.3, RLFD performs the following steps on each packet: (1) a hash computation to find the flow’s path in the tree, (2) a bitwise AND operation to find the subpath down to the depth of the current period, (3) an integer comparison to determine if the flow is part of an active counter, and (4) a counter value update if the flow is hashed into the loaded counter array. Each of these operations is \( O(1) \) complexity and fast enough to compute within 76 CPU cycles.

At the bottom level, after operations (1) to (3), RLFD performs the following steps: (5) a Cuckoo lookup/insert to find the appropriate counter, (6) a counter value update to represent the usage of a flow, (7) a large-flow check that compares the counter value with a threshold, and (8) an on-chip blacklist write if the counter has exceeded the threshold. Steps (5)–(7) are only performed on packets from the small fraction of flows that are loaded in the bottom-level array; step (8) is only for packets of the flows identified as large flows in step (7), and this only happens once for each flow (if we block the large flows in the blacklist). Thus steps (5)–(8) are executed much less frequently than steps (1)–(4). Even so, steps (5)–(8) have a constant time in expectation, and are negligible in comparison with steps (1)–(4).

**Storage complexity.** RLFD only keeps a small array of counters and a few additional variables: the hash function key, the 64-bit mask value for the current level, and the 64-bit identifier of the currently loaded counter array. Because we use Cuckoo hashing at the bottom level, besides a 32-bit field for the counter value, each counter entry needs to have a field for the associated flow ID key, which is 96 bits in IPv4 and 288 bits in IPv6. An array of 128 counters requires 2 KB in IPv4 and 5 KB for IPv6, which readily fits within the L1 cache. As discussed in Appendix A.2, we can further shrink the flow ID field size to 48 bits (with FP probability \( \leq 2^{-38} \) for each flow); if deployed, a 128 counter array is 1.25 KB and a 1024 counter array is 10 KB for both IPv4 and IPv6, which can fit into the L1 cache (32 KB).

### 4.5 RLFD’s Advantages and Disadvantages

**Advantages.** With recursive subdivision and additional optimization techniques, RLFD is able to (1) identify low-rate large flows with non-zero prob-
ability, with probability close to 100% for flows that cause extensive damage (Section 5.3 analyzes RLFD’s detection probability); and (2) guarantee no-FP, eliminating damage due to FP.

**Disadvantages.** First, a landmark-window-based algorithm such as RLFD cannot guarantee exact detection over large-flow specification based on arbitrary time windows [42] (landmark window and arbitrary window are introduced in Section 2.1). However, this approximation results in limited damage, as mentioned in Section 3. Second, recursive subdivision based on landmark time windows requires at least one detection cycle to catch a large flow. Thus, RLFD cannot guarantee low damage for flows with very high rates. Third, RLFD works most effectively when the large flow exceeds the flow specification in all $d$ levels, so bursty flows with a burst duration shorter than the RLFD detection cycle $T_c$ are likely to escape detection (where *burst duration* refers to the amount of time during which the bursty flow sends in excess of the flow specification).

### 4.6 CLEF Hybrid Scheme

We propose a hybrid scheme, CLEF, which is a parallel composition with one EARDet and two RLFDs (Twin-RLFD). This hybrid can detect both high-rate and low-rate large flows without producing FPs, requiring only a limited amount of memory. We use EARDet instead of Flow Memory in this hybrid scheme because EARDet’s detection is deterministic, thus has shorter detection delay.

**Parallel composition of EARDet and RLFD.** As described in Section 3.2, we combine EARDet and RLFD in parallel so that RLFD can help EARDet detect low-rate flat flows, and EARDet can help RLFD quickly catch high-rate flat and bursty flows.

**Twin-RLFD parallel composition.** RLFD is most effective at catching flows that violate flow specification across an entire detection cycle $T_c$. An attacker can reduce the probability of being caught by RLFD by choosing a burst duration shorter than $T_c$ and an inter-burst duration greater than $T_c/d$ (thus reducing the probability that the attacker will advance to the next round during its inter-burst period). We therefore introduce a second RLFD (RLFD(2)) with a longer detection cycle $T_{c(2)}$, so that a flow must have burst duration shorter than $T_{c(1)}$ and burst period longer than $T_{c(2)}/d$ to avoid detection by the Twin-RLFD (where RLFD(1) and $T_{c(1)}$ are the first RLFD and its detection cycle respectively). For a given average rate, flows that evade Twin-RLFD have a higher burst rate than flows that evade a single RLFD. By properly setting $T_{c(1)}$ and $T_{c(2)}$, Twin-RLFD can synergize with EARDet, ensuring that a flow undetectable by Twin-RLFD must use a burst higher than EARDet’s rate threshold $\gamma_h$.

**Timing randomization.** An attacker can strategically send traffic with burst durations shorter than $T_{c(1)}$, but choose low duty cycles to avoid detection by both RLFD(1) and EARDet. Such an attacker can only be detected by RLFD(2), but RLFD(2) has a longer detection delay, allowing the attacker to maximize
damage before being blacklisted. To prevent attackers from deterministically maximizing damage, we randomize the length of the detection cycles $T_c^{(1)}$ and $T_c^{(2)}$.

5 Theoretical Analysis

Table 2: Table of Notations.

| Notation   | Description                                                                 |
|------------|-----------------------------------------------------------------------------|
| $\rho$     | Rate of (outbound) link                                                     |
| $\gamma, \beta$ | Rate and burst threshold flow specification                             |
| $\theta$  | Duty cycle of bursty flows ($\theta \leq 1$)                               |
| $T_b$      | Period of burst                                                             |
| $R_{atk}, \alpha$ | Average large-flow rate, and $R_{atk} = \alpha \gamma$                |
| $n$        | Number of legitimate flows                                                  |
| $n_{\gamma}$ | Maximum number of legitimate flows at rate $\gamma$                     |
| $m$        | Number of counters available in a detector                                |
| $\gamma_h$ | EARDet high-rate threshold rate                                             |
| $E(D_{over})$ | Expected overuse damage                                                     |

RLFD notations:

- $d$ $\triangleq$ Number of levels
- $n^{(k)}$ $\triangleq$ Number of legitimate flows in the level $k$
- $T_t$ $\triangleq$ Time period of a detection level
- $T_c$ $\triangleq$ Detection cycle $T_c = d \cdot T_t$
- $Pr(A_\alpha)$ $\triangleq$ Detection prob. for flows with $R_{atk} = \alpha \gamma$
- $\alpha_{0.5}$ $\triangleq$ When $\alpha \geq \alpha_{0.5}$, approximately $Pr(A_\alpha) \geq 0.5$
- $\alpha_{1.0}$ $\triangleq$ When $\alpha \geq \alpha_{1.0}$, approximately $Pr(A_\alpha) = 1.0$

In this section, we discuss RLFD’s performance and its large-flow detection probability. We then compare CLEF with state-of-the-art schemes, considering various types of large flows under CLEF’s worst-case background traffic. Due to limited space, some derivations are in the appendix.

Detection probability. Single-level detection probability is the probability that a RLFD selects a correct counter (containing at least one large flow) for the next level. Total detection probability is the probability that one copy of RLFD catches a large flow in a cycle $T_c$, which is the product of the single-level detection probabilities across all levels in a cycle, minus the probability that two large flows will be assigned to the highest counter at the last level. The subtrahend is small and negligible when the number of levels is large enough.
5.1 RLFD Worst-case Background Traffic

Since our goal is to minimize worst-case damage, we assume the worst-case background traffic against RLFD in the rest of the analysis. Given a large flow, the worst-case background traffic is the legitimate flow traffic pattern that maximizes damage caused by a large flow. Since damage increases with expected detection delay (and thus decreases with single-level detection probability) in RLFD, we derive the worst-case background traffic by finding the minimum single-level detection probability for each level of RLFD. Theorem 1 states that the worst-case background traffic consists of threshold-rate legitimate flows fully utilizing the outbound link. The proof and discussion of Theorem 1 and are presented in Appendix B.3.

**Theorem 1.** On a link with a threshold rate $\gamma$ and an outbound link capacity $\rho$, given an attack large flow $f_{atk}$, RLFD runs with the lowest probability to select the counter containing $f_{atk}$ to the next level, when there are $n_\gamma = \rho/\gamma$ legitimate flows, each of which is at the rate of $\gamma$.

Figure 11 in Appendix B.3 presents single-level detection probabilities for several different background traffic patterns, which empirically validates our theorem.

5.2 Characterizing Large Flows

To systematically compare CLEF with other detectors under various types of attack flows, we categorize large flows based on three characteristics, as Figure 5 illustrates:

1. **Burst Period** ($T_b$). A large flow sends a burst of traffic in a period of $T_b$.
2. **Duty Cycle** ($\theta \in (0, 1]$). In each period of length $T_b$, a large flow only sends packets during a continuous time period of $\theta T_b$ and remains silent during the rest of the period.
3. **Average Rate** ($R_{atk}$). This is the average volume of traffic sent from a large flow per second over a time interval much longer than the burst period $T_b$. The instant rate during the burst chunk $\theta T_b$ is $R_{atk}/\theta$.

Fig. 5: Flow with average rate $R_{atk}$, burst period $T_b$, duty cycle $\theta \in (0, 1]$. 

...
By remaining silent between bursts, attacks such as the Shrew attack \cite{22} keep the average rate lower than the detection threshold to evade the detection algorithms based on landmark windows \cite{12,13,15,16,19,28–30}.

A large flow may switch between different characteristic patterns over time, including ones that comply with flow specifications. The total damage in this case can be computed by adding up the damage inflicted by the large flow under each appearing pattern. Hence, for the purpose of the analysis, we focus our discussion on large flows with fixed characteristic patterns.

5.3 RLFD Detection Probability for Flat Flows

In order to detect a flat ($\theta = 1$) large flow, the traffic of the flat large flow should be observable in each detection level.

The probability that RLFD catches one large flow in a detection cycle increases with the number of large flows passing through RLFD. Because a greater number of large flows implies that more counters may contain large flows in each level, RLFD has a higher chance of correctly selecting counters with large flows in the recursive subdivision. We therefore discuss the worst-case scenario for RLFD where only one large flow is present.

Because the operation in all but the bottom level of RLFD is similar and the only difference is the flows hashed to the counter array, we discuss the detection in a single level first and expand it to the whole detection cycle. Additional numeric examples are provided in Appendix B.4.

**Single-level detection probability.** Given the total number of flows traversing the link is $n$, we can predict the expected number of flows in the $k$th level by $n^{(k)} = n/m^{k-1}$, where $m$ is the number of counters. Since $n^{(k)}$ depends only on the total number of flows and not the traffic distribution, we discuss a single-level detection with $n^{(k)}$ legitimate flows, $m$ counters, and a large flow at the rate of $R_{atk} = \alpha \gamma$, where $\gamma$ is the threshold rate and $\alpha > 1$. When the context is clear, we use $n$ to stand for $n^{(k)}$ in the discussion of single-level detection.

According to Theorem 1, the worst-case background traffic is that all $n$ legitimate flows are at the threshold rate $\gamma$; Theorem 2 shows an approximate lower bound of the single-level detection probability $P_{worst}(m,n,\alpha)$ in such worst-case background traffic. The proof of Theorem 2 and its Corollaries 1 and 2 are presented in Appendix C.1.

**Theorem 2.** Given $m$ counters in a level, $n$ legitimate flows at full rate $\gamma$, and a large flow $f_{atk}$ with an average rate of $R_{atk} = \alpha \gamma$, the probability $P_{worst}(m,n,\alpha)$ that RLFD will correctly select the counter with large flow $f_{atk}$ has an approximate lower bound of $1 - Q(K, \frac{n}{m})$, where $K = \left\lfloor \frac{n}{m} + \sqrt{\frac{2n}{m} \log n - \alpha} \right\rfloor$; $Q(K, \frac{n}{m})$ is the cumulative distribution function (CDF) of the Poisson distribution $\text{Pois}(\frac{n}{m})$.

**Corollary 1.** For a detection level with $n$ legitimate flows, $m$ counters, and a large flow $f_{atk}$ at the average rate of $\alpha_{0.5} \gamma$, the probability $P_{worst}(m,n,\alpha_{0.5})$ that RLFD will correctly select the counter of $f_{atk}$ has an approximate lower bound of $0.5$, where $\alpha_{0.5} = \sqrt{2 \frac{n}{m} \log n}$. 
Corollary 2. For a detection level with $n$ legitimate flows, $m$ counters, and a large flow $f_{atk}$ at the average rate of $\alpha_{0,1}\cdot \gamma$, the probability $P_{\text{worst}}(m,n,\alpha_{0,0})$ that RLFD will correctly select the counter of $f_{atk}$ has an approximate lower bound of 1.0, where $\alpha_{0,0} = 2 \cdot \alpha_{0,0} = 2c\sqrt{\frac{n}{m}} \log n$.

**Total detection probability.** Theorem 3 describes the total probability of detecting a large flow in one detection cycle. Detailed proof is provided in Appendix C.2.

Theorem 3. When there are $n$ legitimate flows and a flat large flow at the rate of $\alpha\gamma$, the total detection probability of a RLFD with $m$ counters has an approximate lower bound:

\[
Pr(A_\alpha) \geq \begin{cases} 
1 - Q(K, \frac{n_\gamma}{m}) & \text{when } n \geq n_\gamma \\
1 - Q(K, \frac{n}{m}) & \text{when } n < n_\gamma
\end{cases}
\]

(1)

where $K = \left\lceil \frac{n}{m} + \sqrt{2\frac{n}{m} \log n - \alpha_\gamma} \right\rceil$, $K = \left\lceil \frac{n}{m} + \sqrt{2\frac{n}{m} \log n - \alpha} \right\rceil$, and $Q(x, \lambda)$ is the CDF of the Poisson distribution $\text{Pois}(\lambda)$.

5.4 Twin-RLFD Theoretical Overuse Damage

To evaluate RLFD’s performance, we derive a theoretical bound on the damage caused by large flows against RLFD. Recall that there are two sources of damage: FP damage $D_{fp}$ and overuse damage $D_{over}$. Because RLFD has no FP, there is no need to consider $D_{fp}$. Thus, we only theoretically analyze $D_{over}$.

Theorem 4. A Twin-RLFD with RLFD(1) and RLFD(2) whose detection cycles are $T_{c}^{(1)}$ and $T_{c}^{(2)} = \frac{2d_\gamma}{\alpha_{\gamma}} T_{c}^{(1)}$, respectively, it can detect bursty flows at an average rate $R_{atk} = \alpha_{\gamma} < \theta_{\gamma}h$, where $\gamma_h$ is the high-rate threshold rate of the EARDet. The expected overuse damage caused by such flows has the following upper bound:

\[
E(D_{over}) \leq \begin{cases} 
T_{c}^{(1)} \frac{\gamma_h}{\theta} Pr(A_\alpha) & \text{when } \theta T_b \geq 2T_{c}^{(1)} \\
T_{c}^{(1)} \frac{2d_\gamma}{\theta_{\gamma}} Pr(A_\alpha) & \text{when } \theta T_b \leq 2T_{c}^{(1)}
\end{cases}
\]

(2)

where

\[
Pr(A_\alpha) \geq \begin{cases} 
1 - Q(K, \frac{n_\gamma}{m}) & \text{when } n \geq n_\gamma \\
1 - Q(K, \frac{n}{m}) & \text{when } n < n_\gamma
\end{cases}
\]

(3)

and $K = \left\lceil \frac{n}{m} + \sqrt{2\frac{n}{m} \log n - \alpha_\gamma} \right\rceil$, $K = \left\lceil \frac{n}{m} + \sqrt{2\frac{n}{m} \log n - \alpha} \right\rceil$ ($\alpha_0 = \alpha/\theta$ when $\theta T_b \geq 2T_{c}^{(1)}$, and $\alpha_0 = \alpha$ when $\theta T_b < 2T_{c}^{(1)}$). The $d$ is the number of levels in RLFD, and $Q(x, \lambda)$ is the CDF of the Poisson distribution $\text{Pois}(\lambda)$. The damage of flat flow is that in the case of $\theta = 1$ and $\theta T_b \geq 2T_{c}^{(1)}$. 

Title Suppressed Due to Excessive Length 17
We can see that a properly configured Twin-RLFD can detect bursty flows unable to be detected by EARDet (i.e., flows at average rate $R_{atk} = \alpha \gamma < \theta \gamma$).

Table 3: Theoretical Comparison. CLEF outperforms other detectors with lower large flow damage. Damage in megabyte (MB).

| Algorithm   | FP Damage | Low-rate Large Flow | High-rate Large Flow |
|-------------|-----------|---------------------|----------------------|
|             |           | $R_{atk} < 10^4$    | $10^4 \gamma < R_{atk} < 30^5 \gamma$ | $30^5 \gamma \leq R_{atk} < 250^5 \gamma$ |
| Twin-RLFD   | 0         | [512, +∞)          | [158, 512]           | (33, 45)                            |
| EARDet      |           | +∞                  | +∞                   | +∞                                 |
| FM          |           | +∞                  | +∞                  | +∞                                 |
| AMF         |           | +∞                  | +∞                  | +∞                                 |
| CLEF        |           | [512, +∞)          | [158, 512]           | (33, 45)                            |
| AMF-FM      | 0         | +∞                  | +∞                   | +∞                                 |

Comparison in a 40 Gbps link with threshold rate $\gamma = 400$ Kbps. Each of Twin-RLFD, EARDet, FM and AMF has $m = 100$ counters (each of single RLFD has 50 counters), and thus each of CLEF and AMF-FM has 200 counters. In Twin-RLFD and CLEF, detection cycles $T_c^{(1)} = T_c = 0.1$ sec, $T_c^{(2)} = 7.92$ sec, and number of levels is $d = 4$. Attack Flows are busty flows with duty cycle of $\theta = 0.25$.

The reasons for this Twin-RLFD configuration are shown in Appendix B.5.

5.5 Theoretical Comparison

We compare the CLEF hybrid scheme with the most relevant competitor, the AMF-FM hybrid scheme [15], which runs an AMF and a FM sequentially: all traffic is first sent to the AMF and the AMF sends detected large flows (including FPs) to the FM to eliminate FPs. For completeness, we also present the results of individual detectors, including Twin-RLFD, EARDet, AMF, and Flow Memory (FM). Table 3 summarizes the damage inflicted by different large-flow patterns when different detectors are deployed. The damage is calculated according to the analyses of AMF (Appendix B.2), FM (Appendix B.1), EARDet [42], and Twin-RLFD (Section 5.4). Figures 13(c) and 13(e) in Appendix B.5 provide more details about Twin-RLFD’s overuse damage presented in Table 3.

Comparison setting. To compare detectors in an in-core router setting, we allocate only 100 counters for each detector, and we allocate 50 counters for each RLFD in the Twin-RLFD for a fair comparison. Each hybrid scheme has 200 counters in total to ensure fair comparison between hybrid schemes is fair.

We consider both high-rate large flows ($R_{atk} \geq 250^5 \gamma$) and low-rate large flows ($R_{atk} < 250^5 \gamma$). $250^5 \gamma$ is the minimum rate at which detection is guaranteed by EARDet, FM, and AMF-FM. $\frac{d\rho}{m} = \frac{0.25 \times 10^5 \gamma}{100}$. Low-rate large flows are further
divided into three rate intervals for thorough comparison. For each rate interval, we consider the worst-case ($\theta T_b < 2 T_c$) and non-worst-case ($\theta T_b \geq 2 T_c$) burst length. The duty cycle of the bursty flow is set to $\theta = 0.25$, which is challenging for CLEF. Given an average rate $R_{atk}$, if $\theta$ is close to 0 (close to 1), a bursty flow is easily detected by EARDet (Twin-RLFD) in CLEF.

**CLEF ensures lower damage.** As shown in Table 3, Twin-RLFD and CLEF outperform other detectors for identifying a wide range of low-rate flows. However, due to limited memory, it remains challenging for Twin-RLFD and CLEF to effectively detect large flows that are extremely close to the threshold.

We can see that Twin-RLFD fails to limit the damage caused by high-rate large flows, because the overuse damage is linear in $R_{atk}$ of high-rate flows (due to the minimum detection delay of one cycle). Thus, CLEF uses EARDet to limit the damage caused by high-rate flows. CLEF is better than the AMF-FM hybrid scheme. This is because the FP from AMF (with limited memory) is too high to narrow down the traffic passed to the FM in the downstream, so that the FM’s performance is not improved.

![Graph](image)

*Fig. 6: Minimum Rate of Guaranteed Detection $R_{min}$ (shown as $R_{min}/\gamma$ in figures), for flat large flows ($\theta = 1.0$), when link capacity $\rho = 10^5\gamma$ and $10^7\gamma$, where $\gamma$ is threshold rate. Twin-RLFD and CLEF have much lower rate of guaranteed detection than other schemes when the memory is limited.*

**CLEF is memory-efficient.** We now consider the minimum rate of guaranteed detection ($R_{min}$) for flat flows (i.e., flat large flows ($\theta = 1.0$) exceeding the rate $R_{min}$) of these detectors. The $R_{min}$ of Twin-RLFD and CLEF is bounded from above by $4\theta \sqrt{\frac{m \log n_\gamma}{n_\gamma}}$ (derived from Corollary 2), which is much less than the $R_{min} = \theta \frac{\rho}{m+1}$ for EARDet and $R_{min} = \theta \frac{\rho}{m}$ for FM and AMF-FM. This is especially true when the memory is extremely limited (i.e. $n_\gamma \gg m$), where $n_\gamma$ is the maximum number of legitimate flows at the threshold rate $\gamma$, and $m$ is the number of counters for each individual detector (each RLFD in Twin-RLFD has $m/2$ counters).
Figures [6(a)] and [6(b)] compare the $R_{\min}$ amongst these three detectors given two link capacities: 1) $\rho = 10^5\gamma$ (i.e., $n_\gamma = 10^5$), and 2) $\rho = 10^7\gamma$ (i.e., $n_\gamma = 10^7$). The results suggest that Twin-RLFD and CLEF have a much lower $R_{\min}$ than that of other detectors when memory is limited, and the $R_{\min}$ is insensitive to memory size because RLFD can add levels to overcome memory shortage.

For bursty flows, CLEF’s $R_{\min}$ is competitive to AMF-FM, due to EARDet.

6 Evaluation

We experimentally evaluate CLEF, RLFD, EARDet, and AMF-FM with respect to worst-case damage [41, Sec. 5.1]. We consider various large-flow patterns and memory limits and assume background traffic that is challenging for CLEF and RLFD. The experiment results confirm that CLEF outperforms other schemes, especially when memory is extremely limited.

6.1 Experiment Settings

**Link settings.** Since the required memory space of a large-flow detector is sublinear to link capacity, we set the link capacity to $\rho = 1Gbps$, which is high enough to incorporate the realistic background traffic dataset while ensuring the simulation can finish in reasonable time. We choose a very low threshold rate $\gamma = 12.5$ KB/s, so that the number of full-use legitimate flows $n_\gamma = \rho/\gamma$ is 10000, ensuring that the link is as challenging as a backbone link (as analyzed in Section 4.4). The flow specification is set to $TH(t) = \gamma t + \beta$, where $\beta$ is set to 3028 bytes (which is as small as two maximum-sized packets, making bursty flows easier to catch).

The results on this 1Gbps link allow us to extrapolate detector performance to high-capacity core routers, e.g., in a 100Gbps link with $\gamma = 1.25$ MB/s. Because CLEF’s performance with a given number of counters is mainly related to the ratio between link capacity and threshold rate $n_\gamma$ (as discussed in Section 5.3), CLEF’s worst-case performance will scale linearly in link capacity when the number of counters and the ratio between link capacity and threshold rate is held constant. AMF-FM, on the other hand, performs worse as the number of flows increases (according to Appendix B.2 and B.1). Thus, with increasing link capacity, AMF-FM may face an increased number of actual flows, resulting in worse performance. In other words, AMF-FM’s worst-case damage may be superlinear in link capacity. As a result, if CLEF outperforms AMF-FM in small links, CLEF will outperform AMF-FM by at least as large a ratio in larger links.

**Background traffic.** We consider the worst background traffic for RLFD and CLEF: we determine the worst-case traffic according to Theorem 1. Aside from attack traffic, the rest of the link capacity is completely filled with full-use legitimate flows running at the threshold rate $\gamma = 12.5$ KB/s. The total number of attack flows and full-use legitimate flows is $n_\gamma = 10000$. Once a flow has been blacklisted by the large-flow detectors, we fill the idle bandwidth with a
new full-use legitimate flow, to keep the link always running with the worst-case background traffic.

**Attack traffic.** We evaluate each detector against large flows with various average rates $R_{atk}$ and duty cycle $\theta$. Their bursty period is set to be $T_b = 0.967s$. To evaluate RLFD and CLEF against their worst-case bursty flows ($\theta T_b < 2T_c$), large flows are allotted a relatively small bursty period $T_b = 4T_c = 0.967s$, where $T_c = \beta/\gamma = 0.242s$ is the period of each detection level in the single RLFD. In CLEF, RLFD(1) uses the same detection level period $T^{(1)}_c = T_c = 0.242s$ as well. Since RLFD usually has $d \geq 3$ levels and $T_c \geq 3T_c$, it is easy for attack flows to meet $\theta T_b < 2T_c$.

In each experiment, we have 10 artificial large flows whose rates are in the range of 12.5 KB/s to 12.5 MB/s (namely, 1 to 1000 times that of threshold rate $\gamma$). The fewer large flows in the link, the longer delay required for RLFD and CLEF to catch large flows; however, the easier it is for AMF-FM to detect large flows, because there are fewer FPs from AMF and more frequent flow eviction in FM. Thus, we use 10 attack flows to challenge CLEF and the results are generalizable.

**Detector settings** We evaluate detectors with different numbers of counters ($20 \leq m \leq 400$) to understand their performance under different memory limits. Although a few thousands of counters are available in a typical CPU, not all can be used by one detector scheme. CLEF works reasonably well with such a small number of counters and can perform better when more counters are available.

- **EARDet.** We set the low-bandwidth threshold to be the flow specification $\gamma t + \beta$, and compute the corresponding high-rate threshold, $\gamma_h = \frac{\beta}{m+1}$, for $m$ counters as in [42].

- **RLFD.** A RLFD has $d$ levels and $m$ counters. We set the period of a detection level as $T_c = \beta/\gamma = 0.242s$ second [42].

- **CLEF.** We allocate $m/2$ counters to EARDet, and $m/4$ counters to each RLFD. RLFD(1) and EARDet are configured like the single RLFD and the single EARDet above. For the RLFD(2), we properly set its detection level period $T^{(2)}_c$ to guarantee detection of most of bursty flows with low damage. The details of the single RLFD and CLEF are in Table 4 (Appendix D).

- **AMF-FM.** We allocate half of the $m$ counters to AMF and the rest to FM. AMF has four stages (a typical setting in [15]), each of which contains $m/8$ counters. All $m$ counters are leaky buckets with a drain rate of $\gamma$ and a bucket size $\beta$.

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10 If $T_c \ll \beta/\gamma$, it is hard for a large flow to reach the burst threshold $\beta$ in such a short time; if $T_c \gg \beta/\gamma$, the detection delay is too long, resulting in excessive damage.
Fig. 7: Damage (in Bytes) caused by 200-second large flows at different average flow rate $R_{atk}$ (in Byte/s) and duty cycle $\theta$ under detection of different schemes with different number of counters $m$. The larger the dark area, the lower the damage guaranteed by a scheme. Areas with white color are damage equals or exceeds $5 \times 10^8$. CLEF outperforms other schemes in detecting flat flows, and has competitive performance to AMF-FM and EARDet over bursty flows.
6.2 Experiment Results

For each experiment setting (i.e., attack flow configurations and detector settings), we did 50 repeated runs and present the averaged results.

Figure 7(a) to 7(e) demonstrate the damage caused by large flows at different average rates, duty cycles, and number of detector counters during 200-second experiments; the lighter the color, the higher the damage. The damage \( \geq 5 \times 10^8 \) Byte is represented by the color white. Figures 8(a) to 8(e) compare damage

Fig. 8: Damage (in Bytes) caused by 200-second large flows at different average rate \( R_{atk} \) (in Byte/s) and duty cycle \( \theta \). Each detection scheme uses 200 counters in total. The clear comparison among schemes suggests CLEF outperforms others with low damage against various large flows.

Fig. 9: FN ratio in a 200-second detection for large flows at different average rate \( R_{atk} \) (in Byte/s) and duty cycle \( \theta \). Each detection scheme uses 200 counters in total. CLEF is able to detect (FN < 1.0) low-rate flows undetectable (FN = 1.0) by AMF-FM or EARDet.
in cases of different detectors with 200 counters. Figures 9(a) to 9(e) show the  
percentage of FNs produced by each detection scheme with 200 counters within  
200 seconds. We cannot run infinitely-long experiments to show the +∞ damage  
produced by detectors like EARDet and AMF-FM over low-rate flows, so we use  
the FN ratio to suggest it here. An FN of 1.0 means that the detector fails to  
identify any large flow in 200 seconds and is likely to miss large flows in the  
future. Thus, an infinite damage is assigned. On the contrary, if a detector has  
FN rate < 1.0, it is able to detect remaining large flows at some point in the  
future.

**CLEF ensures low damage against flat flows.** Figures 7(a) to 9(a) support our theoretical analysis (in Section 5) that RLFD and CLEF work  
effectively at detecting low-rate flat large flows and guaranteeing low damage. On  
the contrary, such flows cause much higher damage against EARDet and AMF-  
FM. The nearly-black figure (in Figure 7(a)) for CLEF shows that CLEF is  
effective for both high-rate and low-rate flat flows with different memory limits.  
Figure 8(a) shows a clear damage comparison among detector schemes. CLEF,  
EARDet, and AMF-FM all limit the damage to nearly zero for high-rate flat  
flows. However, the damage limited by CLEF is much lower than that limited  
by AMF-FM and EARDet for the low-rate flat flows. EARDet and AMF-FM  
results show a sharp top boundary that reflects the damage dropping to zero at  
the guaranteed-detection rates.

The damage limited by an individual RLFD is proportional to the large-  
flow rate when the flow rate is high. Figure 9(a) suggests that AMF-FM and  
EARDet are unable to catch most low-rate flat flows (\( R_{atk} < 10^6 \) Byte/sec),  
which explains the high damage by low-rate flat flows against these two schemes.  
This supports our theoretical analysis of AMF-FM and EARDet in Table 3: the  
infinite damage by low-rate flows against AMF-FM and EARDet.

**CLEF ensures low damage against various bursty flows.** Figures 8(b) to  
8(e) demonstrate the damage caused by bursty flows with different duty cycle  
\( \theta \). The smaller the \( \theta \) is, the burtier the flow. As the large flows become burstier,  
the EARDet and AMF-FM schemes improve at detecting flows whose average  
rate is low. Because the rate at the burst is \( R_{atk}/\theta \), which increases as \( \theta \) decreases,  
thus EARDet and AMF-FM are able to detect these flows even though their  
average rates are low. For a single RLFD, the burstier the flows are, the harder  
it becomes to detect the large flows and limit the damage. As we discussed in  
Section 4.6 when the burst duration \( \theta T_b \) of flows is smaller than the RLFD  
detection cycle \( T_c \), a single RLFD has nearly zero probability of detecting such  
attack flows. Thus, we need Twin-RLFD in CLEF to detect bursty flows missed  
by EARDet in CLEF, so that CLEF’s damage is still low as the figures show.  
When the flow is very bursty (e.g., \( \theta \leq 0.1 \)), the damage limitation of the CLEF  
scheme is dominated by EARDet.

Figures 8(b) to 8(e) present a clear comparison among different schemes  
against bursty flows. The damage limited by CLEF is lower than that limited by  
AMF-FM and EARDet, when \( \theta \) is not too small (e.g., \( \theta \geq 0.25 \)). Even though  
AMF-FM and EARDet have lower damage for very bursty flows (e.g., \( \theta \leq 0.1 \))
than the damage limited by CLEF, the results are close because CLEF is assisted by an EARDet with m/2 counters. Thus, CLEF guarantees a low damage limit for a wider range of large flows than the other schemes.

**CLEF outperforms others in terms of FN and FP.** To make our comparison more convincing, we examine schemes with classic metrics: FN and FP. Since we know all four schemes have no FP, we simply check the FN ratios in Figures 9(a) to 9(e). Generally, CLEF has a lower FN ratio than AMF-FM and EARDet do. CLEF can detect large flows at a much lower rate with zero FN ratio, and is competitive to AMF-FM and EARDet against very bursty flows (e.g., Figures 9(b) and 9(e)).

**CLEF is memory-efficient.** Figure 7(a) shows that the damage limited by RLFD is relatively insensitive to the number of counters. This suggests that RLFD can work with limited memory and is scalable to larger links without requiring a large amount of high-speed memory. This can be explained by RLFD’s recursive subdivision, by which we simply add one or more levels when the memory limit is low. Thus, we choose RLFD to complement EARDet in CLEF.

In Figure 7(a), CLEF ensures a low damage (shown in black) with tens of counters, while AMF-FM suffers from a high damage (shown in light colors), even with 400 counters. This supports our theoretical results in Figures 6(a) and 6(b).

**CLEF is effective against various types of bursty flows.** Figures 10(a) and 10(b) demonstrate the changes of damage and FN ratio versus different duty cycles θ when CLEF is used to detect bursty flows. In the 200-second evaluation, as θ decreases, the maximum damage across different average flow rates increases first by (θ ≥ 0.1) and then decreases by (θ < 0.1). The damage increases when θ ≥ 0.1 because Twin-RLFD (in CLEF) gradually loses its capability to detect bursty flows. The damage therefore increases due to the increase in detection delay.
However, the maximum damage does not increase all the way as $\theta$ decreases, because when $\theta$ is getting smaller, EARDet is able to catch bursty flows with a lower average rate. This explains the lower damage from large flows in the 200-second timeframe. Figure 10(b) shows that the FN ratio curve changes within a small range as $\theta$ decreases, which also indicates the stable performance of CLEF against various bursty flows. Moreover, the FN ratios are all below 1.0, which means that CLEF can eventually catch large flows, whereas EARDet and AMF-FM cannot.

**CLEF operates at high speed.** We also evaluated the performance of a Golang-based implementation under real-world traffic trace from the CAIDA [7] dataset. The implementation is able to process 11.8M packets per second, which is sufficient for a 10 Gbps Ethernet link, which has a capacity of 14.4M packets per second.

## 7 Related Work

The most closely related large-flow detection algorithms are described in Section 3.1 and compared in Sections 5 and 6. This section discusses other related schemes.

**Frequent-item finding.** Algorithms that find frequent items in a stream can be applied to large-flow detection. For example, Lossy Counting [28] maintains a lower bound and an upper bound of each item’s count. It saves memory by periodically removing items with an upper bound below a threshold, but loses the ability to catch items close to the threshold. However, the theoretical memory lower bound of one-pass exact detection is linear to the number of large flows, which is unaffordable by in-core routers. By combining a frequent-item finding scheme with RLFD, CLEF can rapidly detect high-rate large flows and confine low-rate large flows using limited memory.

**Collision-rich schemes.** To reduce memory requirement in large-flow utilization, a common technique is hashing flows into a small number of bins. However, hash collisions may cause FPs, and FPs increase as the available memory shrinks. For example, both multistage filters [14, 15] and space-code Bloom filters [21] suffer from high FPs when memory is limited.

**Sampling-based schemes.** Sampling-based schemes estimate the size of a flow based on sampled packets. However, with extremely limited memory and thus a low sampling rate, neither packet sampling (e.g., Sampled Netflow [11]) nor flow sampling (e.g., Sample and Hold [15] and Sticky Sampling [28]) can robustly identify large flows due to insufficient information. In contrast, RLFD in CLEF progressively narrows down the candidate set of large flows, thereby effectively confining the damage caused by large flows.

**Top-k detection.** Top-k heavy hitter algorithms can be used to identify flows that use more than $1/k$ of bandwidth. Space Saving [29] finds the top-k frequent items by evicting the item with the lowest counter value. HashPipe [36] im-
proves upon Space Saving so that it can be practically implemented on switching hardware. However, HashPipe still requires keeping 80KB to detect large flows that use more than 0.3% of link capacity, whereas CLEF can enforce flow specifications as low as $10^{-6}$ of the link capacity using only 10KB of memory. Tong et al. [37] propose an efficient heavy hitter detector implemented on FPGA but the enforceable flow specifications are several orders looser than CLEF. Moreover, misbehaving flows close to the flow specification can easily bypass such heavy hitter detectors. The FPs caused by heavy hitters prevent network operators from applying strong punishment to the detected flows.

Chen et al. [9] and Xiao et al. [43] propose memory-efficient algorithms for estimating per-flow cardinality (e.g., the number of packets). These algorithms, however, cannot guarantee large-flow detection in adversarial environments due to under- or over-estimation of the flow size.

Liu et al. [26] propose a generic network monitoring framework called UniMon that allows extraction of various flow statistics. It creates flow statistics for all flows, but has high FP and FN when used to detect large flows.

8 Conclusion

In this paper we propose new efficient large-flow detection algorithms. First, we develop a randomized Recursive Large-Flow Detection (RLFD) scheme, which uses very little memory yet provides eventual detection of persistently large flows. Second, we develop CLEF, which scales to Internet core routers and is resilient against worst-case traffic. None of the prior approaches can achieve the same level of resilience with the same memory limitations. To compare attack resilience among various detectors, we define a damage metric that summarizes the impact of attack traffic on legitimate traffic. CLEF can confine damage even when faced with the worst-case background traffic because it combines a deterministic EARDet for the rapid detection of very large flows and two RLFDs to detect near-threshold large flows. We proved that CLEF is able to guarantee low-damage large-flow detection against various attack flows with limited memory, outperforming other schemes even with CLEF’s worst-case background traffic. Further experimental evaluation confirms the findings of our theoretical analysis and shows that CLEF has the lowest worst-case damage among all detectors and consistently low damage over a wide range of attack flows.

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A Additional Details For RLFD Data Structure and Optimization

A.1 Analysis for No-FP Guarantee

To guarantee no FP, we only identify large flows whose counter has no second flow, i.e. no flow hash collision $C_{\text{free}}$. If we randomly hash flows into counters at the bottom level $L_d$, the no-collision probability for a counter is $Pr(C_{\text{free}}) = \left[\frac{m-1}{m}\right]^{n_d-1}$, where $n_d$ is the number of flows selected into $L_d$. Because we want to have $d$ as small as possible, thus, we usually may choose $d = \lceil \log_m n \rceil$, where $n$ is the total number of flows in the link. Thus, $n_d \leq m$ on average. Thus,

$$Pr(C_{\text{free}}) = \left[\frac{m-1}{m}\right]^{n_d-1} \approx e^{-\frac{n_d-1}{m}} \quad (4)$$

When $n_d \approx m$, the no-collision probability $Pr(C_{\text{free}}) \approx \frac{1}{e} = 0.368$, which gives a collision probability for each flow of 0.632.

To avoid the high collision probability in the regular hash above, we randomly pick $m$ flows (out of $n_d$ flows) instead. Each of $m$ flows is monitored by a dedicated counter (which does not introduce additional FNs, because $n_d \leq m$). To efficiently implement this counter assignment, we can use Cuckoo hashing [33] to achieve constant expected flow insertion time and worst-case constant lookup and update time. Cuckoo hashing resolves collisions by using two hash functions instead of only one in regular hashing. As in [31], Mitzenmacher shows that, with three hash functions, Cuckoo hashing can achieve expected constant insertion and lookup time with load factor of 91%. Thus, when $m = n_d$, the Cuckoo hashing can achieve $Pr(C_{\text{free}}) \approx 0.91$, which is still much larger than $Pr(C_{\text{free}}) \approx 0.368$ in the regular hashing. As $n_d$ is usually less than $m$ (because we set $d$ to be the ceiling of $\log_m n$), it is reasonable to treat the $Pr(C_{\text{free}}) \approx 1$ in our later analysis. Cuckoo hashing requires to store both the key (48 bits for IPv4, 144 bits for IPv6) and value (32 bits) of an entry, thus, for each counter, we need space for the flow ID and the counter value.

A.2 Shrinking Counter Entry Size

As we discussed, the number of flows hashed into the bottom level is much less than $m$ (e.g. at most $2^{10}$). a key space of 96 bits (288 for IPv6) is too large for less than $2^{10}$ keys. We can hash the flow IDs into a smaller key space, e.g. 48 bits to save memory size. For each flow, although hash collision could happen and may result in FP in the detection in the bottom level, the probability is less than $1 - \left[\frac{4^8-1}{2^{48}}\right]2^{10} \approx 2^{-38}$ which is very small. For systems can tolerate such extremely low FP probability, we recommend it to do so.
B Additional Analysis

B.1 Flow Memory Analysis

We analyze the Flow Memory (FM) with random flow eviction mechanism, which is applied with multistage filters in [15]. For each incoming packet whose flow is not tracked, such FM randomly picks a flow from the tracked flows and the new flow to evict. Thus, for each packet of the flow not tracked, the existing tracked flow has a probability \( P_e = \frac{1}{m+1} \) to be evicted, where \( m \) is the number of counters in the FM.

**Theorem 5.** In a link with total traffic rate of \( R \) (\( \leq \rho \)), the packet size of \( S_{pkt} \), and the large-flow threshold \( TH(t) = \gamma t + \beta \), a Flow Memory with \( m \) counters is able to detect large flows at rate around or higher than \( \frac{\beta}{S_{pkt}} \frac{R}{m} \) with high probability.

**Proof sketch:** We assume number of packets arriving at the FM per second is at the packet rate of \( R_{\text{pkt}} \), thus the time gap between two incoming packets is \( T_{\text{pkt}} = \frac{1}{R_{\text{pkt}}} = \frac{S_{\text{pkt}}}{R} \). For a newly tracked flow \( f \) at time stamp 0, the \( k \)th eviction happens at \( k \cdot T_{\text{pkt}} \), and \( P_e = \frac{1}{m+1} \) is the probability that flow \( f \) is evicted at the \( k \)th eviction. Evictions are not triggered by packets of flows being tracked, however the number of flows untracked is far larger than the number of flows being tracked, thus we can approximate treat the time gap between evictions as \( T_{\text{pkt}} \). Thus, the expected time length for the flow \( f \) to be tracked is

\[
E(T_{\text{track}}) = \sum_{k=1}^{+\infty} P_e (1 - P_e)^{k-1} k T_{\text{pkt}} = \lim_{k \to +\infty} (1 - P_e) \left( \frac{1 - (1 - P_e)^k}{P_e} - (k + 1)(1 - P_e)^k \right) T_{\text{pkt}} = \frac{1 - P_e}{P_e} T_{\text{pkt}} = m \cdot T_{\text{pkt}}
\]

(5)

As the FM uses leaky bucket counters to enforce the large-flow threshold \( TH = \gamma t + \beta \) (defined in Section 2.1), the counter threshold is the burst threshold \( \beta \). Thus, to detect a large flow at traffic rate of \( R_{atk} \), the FM requires the large flow being tracked at least for a time of \( \beta / R_{atk} \), otherwise the counter value cannot reach the threshold. Therefore,

\[
R_{atk} > \frac{\beta}{E(T_{\text{track}})} = \frac{\beta}{m \cdot T_{\text{pkt}}} = \frac{\beta}{S_{\text{pkt}} \frac{R}{m}}
\]

(6)

Thus for the large flows at rates far smaller than the \( \frac{\beta}{S_{\text{pkt}} \frac{R}{m}} \) are likely to be evicted before violating the threshold \( \beta \).

In the practice, the packet size is not fixed, but we treat it with fixed size for analyzing the least \( R_{atk} \) changes along with the \( m \). Because the real packet size
is also limited in 1514 Bytes, the $\frac{\beta}{S_{\text{pkt}}}$ is a bounded factor. As the $\beta$ is usually larger than the maximum packet size, the $\frac{\beta}{S_{\text{pkt}}} > 1$ for sure.

We can see the scale of the large flow rate can be detected by FM is similar to that can be detected by EARDet (i.e., $\frac{\rho}{m+1}$, where $\rho$ is the link capacity). They both increase as $\frac{1}{m}$ increases. In the worst case of the FM, when the traffic rate is at link capacity ($R = \rho$), the least detectable average rates $R_{\text{atk}}$ of the FM and the EARDet are at the same scale. One difference between them is that the EARDet can guarantee deterministic detection, while the Flow Memory detects flows probabilistically. Our simulations in Section 6 support the analysis above.

### B.2 Multistage Filter Analysis

According to the theoretical analysis in [15], a $m$-counter multistage filter with $d$ stages each of which has $m/d$ counters, the probability for a flow hashed into a counter in each stage without collision ($C_{\text{free}}$) to other flows is as follows. We let $m' = m/d$, and assume there are $n$ flows in total, then

$$
Pr(C_{\text{free}}) = 1 - (1 - (1 - (1 - \frac{1}{m'}))^{n-1})^d
= 1 - (1 - (1 - \frac{1}{m'})^{m'(n-1)})^d
\approx 1 - (1 - e^{-\frac{n-1}{m'}})^d
\to 0, \text{ when } n \to +\infty
$$

(7)

where we assume the $m' \gg 1$ and $n/m' \gg 1$. The assumptions are reasonable: 1) the number of counters $m$ is usually around hundreds, and the $d$ is typically chosen as 4 in [15], therefore $m' \gg 1$; 2) we aim to use very limited counters to detect large flows from a large number of legitimate flows, thus $n/m' \gg 1$.

In the case that every legitimate flow is higher than the half of the threshold rate $\gamma/2$, the false positive rate is almost 100%, because the $Pr(C_{\text{free}})$ is close to 100%. Any collision in a counter results in that the counter value violates the counter threshold and thus a falsely positive on legitimate flows.

### B.3 RLFD Worst-case Background Traffic

**General case: weighted balls-into-bins problem.** In the well-known balls-into-bins problem, we have $m$ bins and $n$ balls. For each ball, we randomly throw it into one of $m$ bins.

We treat the flows in the network as the balls, and the counter array as the bins. Hashing flows into counters is just like randomly throwing balls into bins, where each flow is a weighted ball with weight of its traffic volume sent during a period $T_\ell$ of each level $L_k$ ($1 \leq k \leq d$).

**Worst case: single-weight balls-into-bins problem** We assume the rate threshold $\gamma$ of our flow specification, $TH(t) = \gamma t + \beta$, is $\gamma = \frac{\rho}{N}$, where the $\rho$ is the outbound link capacity. In the general case, the legitimate flows are at average
rates less than or equal to the threshold rate $\gamma$, however we show that the worst case background traffic for RLFD to detecting a large flow is that all legitimate flows are sending traffic at the rate of the threshold rate $\gamma$ (Theorem 1). As the inbound link capacity can be larger than the outbound one, there still could be attack flows in this case. We prove the Theorem 1 by the Theorem 6 from Berenbrink et al. which is for weighted balls-into-bins games.

**Theorem 6. Berenbrink et al.’s Theorem 3.1** For two weighted balls-into-bins games $B(w,n,m)$ and $B'(w',n,m)$ of $n$ balls and $m$ bins, the vectors $w = (w_1, ..., w_n)$ and $w' = (w'_1, ..., w'_n)$ represent the weight of each ball in two $B$ and $B'$, respectively. If $W = \sum_{i=1}^{n} w_i = \sum_{i=1}^{n} w'_i$ and $\sum_{i=1}^{k} w_i \geq \sum_{i=1}^{k} w'_i$ for all $1 \leq k \leq n$, then $E[S_i(w)] \geq E[S_i(w')]$ for all $1 \leq i \leq m$, where the $S_i(w)$ is the total load of the $i$ highest bins, and the $E(S_i(w))$ is the expected $S_i(w)$ across all $m^n$ possible balls-into-bins combinations.

**Lemma 1 and Proof sketch**

**Lemma 1.** The RLFD has the lowest probability to correctly select the counter of a large flow $f_{atk}$ to the next level, when the legitimate flows use up all legitimate bandwidth.

We assume $C_1$ and $C_2$ are two different counter states after adding the attack traffic and the traffic of some legitimate flows, and there are $V$ more volume of traffic allowed to send by the other legitimate flows before the total volume of legitimate flows reaches the outbound link capacity. Let $V_{atk}$ be the value of the counter assigned to $f_{atk}$, and the $V_{max}$ be the maximum value of other counters. In the $C_1$, we let $V_{atk} > V_{max} + V$; in the $C_2$, we let $V_{atk} \leq V_{max} + V$. Hence, $C_1$ and $C_2$ cover all possible counter states. As there are still up to $V$ volume of legitimate flows can be added into counters. We use $V'_{atk}$ and $V'_{max}$ to represent the final value of $V_{atk}$ and $V_{max}$. Thus, the probability to select the counter of $f_{atk}$ is

$$Pr(V'_{atk} > V'_{max}) = Pr(V'_{atk} > V'_{max}|C_1)Pr(C_1) + Pr(V'_{atk} > V'_{max}|C_2)Pr(C_2) \quad (8)$$

Because $V_{atk} > V_{max} + V$ in $C_1$, and the $V'_{max}$ cannot exceed $V_{max} + V$, thus always $V_{atk} > V'_{max}$. Then,

$$Pr(V'_{atk} > V'_{max}) = Pr(C_1) + Pr(V'_{atk} > V'_{max}|C_2)Pr(C_2) \quad (9)$$

Let $x$ be the amount of legitimate traffic added into counters after $C_2$, where $0 \leq x \leq V$. If the $x = V$, then there is a chance to have all $V$ added on the $V_{max}$, and thus $V'_{max} = V_{max} + V = V_{atk} = V'_{atk}$, so that $Pr(V'_{atk} > V'_{max}|C_2)$ is lower than that when $x < V$. Therefore, $Pr(V'_{atk} > V'_{max})$ is lower in the case that legitimate flows fully use the link capacity than other cases. Thus, the Lemma 1 is proved.
Proof sketch of Theorem 1. We first just consider the legitimate traffic but not the attack flow. As Lemma 1 illustrated, the more traffic sent from legitimate flows, the harder for RLFD to correctly select the counter with the attack flow $f_{atk}$, thus to have the worst RLFD detection probability, legitimate flow should use all outbound link capacity, and it requires the flow number $n \geq \rho/\gamma$.

Given $n \geq \rho/\gamma$ and $m$, we first construct a legitimate flow configuration $B(w, n, m)$, $w_i = \gamma$ for $1 \leq i \leq \rho/\gamma$ and $w_i = 0$ for $i > \rho/\gamma$ which is the worst-case legitimate configuration we want to prove, because there are actually only the first $\rho/\gamma$ flows with non-zero rate. For any legitimate flow configuration $B'(w', n, m)$ with constraint of $\sum_{i=1}^{k} w'_i = \rho$. It is easy to find $\sum_{i=1}^{k} w_i \geq \sum_{i=1}^{k} w'_i$.

Thus, according to Theorem 6, the $E[S_i(w)] \geq E[S_i(w')]$ for all $1 \leq i \leq m$, where $E[S_i(w)]$ is the expected total counter value of the $i$ highest counters in the case of $B(w, n, m)$ and $E[S_i(w')]$ is the one in the case of any other legitimate flow configuration $B'(w', n, m)$.

It is not hard to find that the $E[S_i(w)] \geq E[S_i(w')]$ for all $1 \leq i \leq m$ suggests that the variation of expected counter values across all counters of the $B(w, n, m)$ is larger than that of the $B'(w', n, m)$. Let $V_{max}$ be the maximum counter value, and $V_{atk}$ be the value of the counter randomly assigned to the attack flow $f_{atk}$ ($V_{atk}$ does not count the traffic of $f_{atk}$). The higher the variation, the larger the expected $V_{max} - V_i$, thus the harder for RLFD to correctly select the counter of $f_{atk}$ for the next level.

Therefore, the $B(w, n, m)$ is the worst legitimate flow configuration for RLFD to detect large flows. ■

Fig. 11: RLFD’s single-level detection probability of the 1st level against a large flow at different rate $R_{atk} = \alpha \gamma$, when background legitimate flows at various rates (0.01 $\gamma$, 0.1 $\gamma$, and $\gamma$) fully use the link capacity of 1000 $\gamma$. The RLFD suffers the lowest detection probability when the legitimate flows are at the threshold rate $\gamma$. 

Detection Probability in a Single Level

| Probability | 100000 flows; background rate = 0.01 |
|-------------|--------------------------------------|
| α = R_{atk}/\gamma | 0 | 0.5 | 1 | 1.5 |
| 0 | 5 | 10 | 15 | 20 |

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B.4 Numeric Analysis For RLFD Detection Probability

![Figures showing probability distributions for different parameter values](image)

Fig. 12: The probability $P_{\text{worst}}(m, n, \alpha)$ when $n$ full-use legitimate flows (at rate of $\gamma$), $m$ counters, and a large flow at the rate of $R_{\text{atk}} = \alpha \cdot \gamma$.

**Numeric analysis for single-level detection.** For each theoretical result, we show numeric examples in the scenario of $n, \gamma = 10^5$ and $m = 100$, an even more memory-limited setting than the one in the complexity analysis (Section 4.4).
Fig. 13: Twin-RLFD worst-case expected overuse damage $E(D_{\text{over}})$ (in MBytes) and its upper bound for flat/bursty flows in various duty cycles $\theta$, burst periods $T_b$, and average rates $R_{\text{atk}} = \alpha \gamma$, in the 40 Gbps link with threshold rate $\gamma = 400$ Kbps ($n_\gamma = 10^5$ full-use legitimate flows at most). The Twin-RLFD has a limited memory of $m = 100$ counters ($50$ counters for each RLFD), a typical number of levels $d = 4$, and detection cycle $T_c^{(1)} = 0.1$ sec, $T_c^{(2)} = 7.92$ sec for two RLFDs respectively. Flows at the EARDet detectable rate $R_{\text{atk}} \geq \theta \gamma h = \theta \frac{\gamma}{m+1}$ are detected by the EARDet with $m = 100$ counters in nearly zero damage.

Figures 12(a) to 12(j) comprehensively shows the simulated worst-case detection probability $P_{\text{worst}}(m, n, \alpha)$ in a level and its lower bound for various number of full-use legitimate flows $n \leq n_\gamma$ (50 to $10^5$). We also give the numeric results with different $m$ (100 and 1000) for comparison. When $n = 10^5$, $m = 100$, we can see $\alpha_{0.5} = 152$ and $\alpha_{1.0} = 303$, which are far smaller than EARDet’s lowest detectable $\alpha = \frac{\rho}{\gamma(m+1)} = \frac{n_\gamma}{m+1} = 991$. For RLFD, the $\alpha$ with actual worst-case detection probability of 0.5 and 1.0 are around 75 and 150, respectively, which are much lower than the $\alpha_{0.5}$ and $\alpha_{1.0}$. Thus, it suggests RLFD’s ability of detecting low-rate large flows. The figures also show that the probability of detecting low-rate flows increases as the number of flows ($n$) decreases or the number of counters ($m$) increases. The figures show that the $\alpha_{0.5}$, $\alpha_{1.0}$, and the lower bound holds for $n > m$, because we derive it with the assumption of $n \gg m \log m$. When $n \leq m$, RLFD has 100% detection probability as explained in Section 4.

Since $\alpha_{1.0}$ decreases rapidly when $n$ decreases, we approximate the total detection probability by the detection probability of the first few levels.
Numeric analysis for total detection probability. In a tough scenario with $n_\gamma = 10^5$, $m = 100$, and $n = 10^7$ legitimate flows in a link during one detection cycle (around a second), RLFD has at least 0.25 and 1.0 probability to detect a flat large flow with $\alpha = 152$ and 303, respectively; and the simulation results suggest that RLFD can detect a large flow with $\alpha = 75$ and 150 with probability around 0.25 and 1.0, respectively. Again, EARDet can only guarantee to detect $\alpha \geq \frac{n_\gamma}{(m+1)} = \frac{n_\gamma}{m+1} = 991$. That is, RLFD outperforms the exact detection algorithm on low-rate large flows.

![Fig. 14: RLFD Total Detection Probability. $n_\gamma = n = 10^5$, $m = 100$.](image)

Figure 14 shows an example of simulated worst-case total detection probability $Pr(A_\alpha)$ and its theoretical lower bound (Theorem 3), when $n_\gamma = n = 10^5$ and $m = 100$. The lower bound holds for the most of $\alpha$, except some very small ones whose $Pr(A_\alpha)$ is close to 0.

B.5 Numeric Analysis For Twin-RLFD Theoretical Overuse Damage

Figures 13(a) to 13(e) show the expected overuse damage $E(D_{over})$ calculated in the worst case and its upper bound from Theorem 4 in a 40 Gbps link with threshold rate $\gamma = 400$ Kbps ($n_\gamma = 10^5$ full-use legitimate flows at most). The Twin-RLFD has $m = 50$ counters for each RLFD, $d = 4$ levels, and detection cycle $T_c^{(1)} = 0.1$ sec and $T_c^{(2)} = 7.92$ sec for two RLFDs, respectively. Damages by large flows with various duty cycles $\theta$ and burst periods $T_b$ are shown. Flows with an average rate $R_{atk}$ higher than $\theta \gamma_h$ (black dash line) will be detected instantly by EARDet (with 100 counters) with nearly zero damage.

The Twin-RLFD has $d = 4$ so that the number of virtual counters in the RLFD bottom level ($m^d = 50^4 = 6.25 \times 10^6$) is larger than the number of flows. Therefore, we the flows selected to the bottom level is fewer than the counters, and RLFD can track each flow individually in the bottom level.
We set $T_c^{(1)} = T_c = 0.1$ sec around $\frac{\beta}{\gamma} = \frac{2 \times 1514}{1514000 \text{ Kbps}} = 0.06$ sec ($\beta$ is usually a few times of maximum packet size 1514 Bytes, so that bursty flows are easier to catch). If $T_c \ll \beta/\gamma$, it is hard for a large flow to reach burst threshold; if $T_c \gg \beta/\gamma$, the detection delay is too long, resulting in excessive damage.

For Twin-RLFD's second RLFD, $T_c^{(2)} = \frac{2d\gamma h}{\alpha\gamma} T_c^{(1)} = 7.92$ sec (according to Theorem 4). Therefore, Twin-RLFD can guarantee detection for the worst-case bursty flows ($\theta T_b < 2T_c^{(1)}$) at rate $R_{atk} \geq \alpha \gamma = 100 \gamma$. We can guarantee detection of lower rate flows with worst-case burstiness by increasing $T_c^{(2)}$; however, increased $T_c^{(2)}$ increases the damage caused by worst-case bursty flows. We say bursty flows with $\theta T_b < 2T_c^{(1)}$ are the worst-case bursty flows, because such flows are unlikely showing up in every level of the RLFD with cycle ($T_c^{(1)}$), so that we have to use the RLFD with longer detection cycle ($T_c^{(2)}$) to catch those flows, which requires longer delay, thus higher damage. Furthermore, such worst-case flows can inflict more damage by increasing $\theta$ (thus the average rate), but remain undetectable by EARDet. As discussed in Section 4.6, we can use choose different $T_c^{(2)}$ randomly in different cycles to prevent attackers from deterministically maximizing damage.

A hybrid scheme consisting of EARDet and Twin-RLFD can limit the worst-case damage caused by flat flows ($\theta = 1$) and bursty flows ($\theta < 1$). Specifically, for flows with an average rate larger than $30\gamma$ (i.e. 12 Mbps), the damage is as low as tens of MBytes (less than ten MBytes for flat flows). We admit that Twin-RLFD cannot limit the damage for flows at extremely low rate ($\ll 30\gamma$) as effectively as for other flows, however other existing schemes cannot neither, because of the limited memory. For flows at high rates, although the Twin-RLFD detects them with almost 100% probability in one detect cycle, it requires at least one cycle to finish detection, hence the damage increases linearly with the flow rate.

Twin-RLFD and EARDet complement each other. Twin-RLFD can detect flows with an average rate lower than $\theta_\gamma h$ but it incompetent at detecting high-rate flows, whereas EARDet is the opposite.

C Proof Sketches

C.1 Proof Sketch For RLFD Single-level Detection Probability

**Proof sketch of Theorem 2** In the analysis, we treat hashing flows into counters as uniformly assigning $n$ legitimate flows into counters and pick a counter for the large flow $f_{atk}$ at random. We denote the random variable of the maximum number of legitimate flows assigned to a counter as $Y$ and the random variable of the number of legitimate flows in the counter of the large flow $f_{atk}$ as $X$.

Because the RLFD pick the counter with the largest value for the next level, thus as long as the value of the large-flow counter $(R_{atk} + X \cdot \gamma)T$ is higher than
the value of the maximum-value legitimate counter \( Y \cdot \gamma T \), the large-flow counter will be picked, where \( T \) is the time length of the level. Then we get

\[
P_{\text{worst}}(m, n, \alpha) = \Pr(R_{\text{atk}} + X \cdot \gamma - Y \cdot \gamma > 0) = \Pr(Y - X < \alpha) = \sum_y \Pr(y - X < \alpha | Y = y) \cdot \Pr(Y = y)
\]

As we discussed in Section B.3, the distributions of \( X \) and \( Y \) are the same as those of the \( X_b \) and \( Y_b \) in a single-weight balls-into-bins game with \( n \) balls and \( m \) bins, where the \( X_b \) is the random variable of the number of balls in a randomly picked bin, and the \( Y_b \) is the random variables of the maximum number of balls in a counter. Thus, we can apply Theorem 7 (by Raab and Steger [34]) to calculate the \( y_{\text{max}} \), the upper bound of \( Y \) at high probability.

**Theorem 7. Raab and Steger’s Theorem 1.** Let \( Y \) be the random variable that counts the maximum number of balls in any bin, if we throw \( n \) balls independently and uniformly at random into \( m \) bins. Then \( \Pr(Y > y_{\text{max}}) = o(1) \), if \( y_{\text{max}} = \frac{n}{m} + \lambda \sqrt{\frac{2}{m} \log n} \), \( \lambda > 1 \), \( m \log m \ll n \leq m \cdot \text{polylog}(m) \), and \( n \) is very large. When \( n \to \infty \), \( o(1) \to 0 \).

We think it is a good approximation to our large-flow problem. Because the number of legitimate flows \( n \) in a backbone link is more than a million, while the number of counters \( m \) is quite limited (e.g. one thousand counters in L1 cache), thus we say \( m \log m \ll n \leq m \cdot \text{polylog}(m) \) and \( n \) is very large. We derive the approximate lower bound of \( P_{\text{worst}}(m, n, \alpha) \) as follows:

\[
P_{\text{worst}}(m, n, \alpha) = \sum_y \Pr(y - X < \alpha | Y = y) \cdot \Pr(Y = y)
\]

\[
= \sum_{y \leq y_{\text{max}}} \Pr(X > y - \alpha, Y = y) + \sum_{y > y_{\text{max}}} \Pr(X > y - \alpha, Y = y)
\]

\[
\geq \sum_{y \leq y_{\text{max}}} \Pr(X > y_{\text{max}} - \alpha, Y = y) + \sum_{y > y_{\text{max}}} \Pr(X > y - \alpha, Y = y)
\]

\[
= \Pr(X > y_{\text{max}} - \alpha) \cdot \Pr(Y \leq y_{\text{max}}) + \sum_{y > y_{\text{max}}} \Pr(X > y - \alpha, Y = y)
\]

We prove that the second part is \( o(1) \) as follows,

\[
\sum_{y > y_{\text{max}}} \Pr(X > y - \alpha, Y = y) \leq \sum_{y > y_{\text{max}}} \Pr(X > y_{\text{max}} - \alpha, Y = y)
\]

\[
= \Pr(X > y_{\text{max}} - \alpha) \cdot \Pr(Y > y_{\text{max}} - \alpha) = \Pr(X > y_{\text{max}} - \alpha) \cdot o(1) = o(1)
\]

\footnote{Raab et al. also provides a similar \( y_{\text{max}} \) for \( m(\log m)^3 \ll n \), but it is enough to only discuss one of them for an approximate result.}
According to Equation 11 and 12, we get

\[ P_{\text{worst}}(m,n,\alpha) \geq \Pr(X > y_{\text{max}} - \alpha) \cdot \Pr(Y \leq y_{\text{max}}) + o(1) \]

\[ = \Pr(X > y_{\text{max}} - \alpha) \cdot \left[ 1 - \Pr(Y > y_{\text{max}}) \right] + o(1) \]

\[ = \Pr(X > y_{\text{max}} - \alpha) \cdot (1 - o(1)) + o(1) \]

\[ \approx \Pr(X > y_{\text{max}} - \alpha) \] (13)

Therefore, when \( n \) is large, we approximately have \( P_{\text{worst}}(m,n,\alpha) \geq \Pr(X > y_{\text{max}} - \alpha) \).

We let \( \eta = \lceil y_{\text{max}} - \alpha \rceil \), and use random variable \( M_k \) to denote the number of bins exactly contain \( k \) balls. We calculate \( \Pr(X > y_{\text{max}} - \alpha) \) as follows,

\[
\Pr(X > y_{\text{max}} - \alpha) = \Pr(X > \eta) = \sum_{k \geq \eta} \Pr(M_k = m_k) = \sum_{k \geq \eta} \frac{m_k}{m} \Pr(M_k = m_k) = \sum_{k \geq \eta} \frac{E(M_k)}{m} \]

\[ = \sum_{\eta \leq k \leq n} \frac{1}{m} \cdot \frac{n!}{k!(n-k)!} \left( m - 1 \right)^{n-k} \]

\[ = \sum_{\eta \leq k \leq n} \binom{n}{k} \left( 1 - \frac{1}{m} \right)^{n-k} \left( \frac{1}{m} \right)^k \] (14)

The above result requires to calculate the sum of the last \( m-\eta + 1 \) items from the binomial distribution \( B(n, \frac{1}{m}) \). As we know, there is no simple, closed forms for Equation 14. According to the law of rare events [8], binomial distribution \( B(n, p) \) is approximate to Poisson distribution \( \text{Pois}(np) \), when \( n \) is large and \( p \) is small. According to Equation 19, the detection probability \( \Pr(A_{\alpha}) \) is mainly related to non-bottom levels in which the number of flows \( n \) is large \((n > m)\), and \( p = \frac{1}{m} \) is small because \( m \) is around hundreds to thousands, we approximately treat \( B(n, \frac{1}{m}) \) as the Poisson distribution \( \text{Pois}(\frac{n}{m}) \), then we have

\[ \binom{n}{k} \left( 1 - \frac{1}{m} \right)^{n-k} \left( \frac{1}{m} \right)^k \approx e^{-\frac{n}{m}} \left( \frac{n}{m} \right)^k k! \] (15)

, which is the probability of the item happens \( k \) times in the Poisson distribution. Then, the Equation 14 turns to
\[
Pr(X > y_{\text{max}} - \alpha) = \sum_{\eta \leq k \leq n} \binom{n}{k} (1 - \frac{1}{m})^{n-k} \left(\frac{1}{m}\right)^k
\]
\[
= \sum_{\eta \leq k \leq n} e^{-\frac{n}{m}} \left(\frac{n}{m}\right)^k \frac{1}{k!} = 1 - Q(\eta - 1, \frac{n}{m})
\]  
(16)

, where \(Q(K, \frac{n}{m})\) is the cumulative distribution function (CDF) of the Poisson distribution \(\text{Pois}(\frac{n}{m})\), i.e. sum of probabilities for \(0 \leq k \leq K\). As the Theorem\(^7\) holds when \(\lambda > 1\), thus we choose \(\lambda \to 1^+\), thus \(y_{\text{max}} = \frac{n}{m} + \sqrt{2\frac{n}{m} \log n}\). Because we focus on how does the probability lower bound change along with the \(m\) and \(n\), the \(\lambda\) does not matter much here. Therefore, we proved that the 

\(1 - Q(K, \frac{n}{m})\) is an approximate lower bound for \(P_{\text{worst}}(m, n, \alpha)\), where \(K = \eta - 1 = \left\lfloor \frac{n}{m} + \sqrt{\frac{2n}{m} \log n - \alpha} \right\rfloor\).

**Proof sketch of Corollary 1.** According to Theorem\(^2\) \(P_{\text{worst}}(m, n, \alpha_{0.5}) > 1 - Q(K, \frac{n}{m})\) approximately, where \(K = \left\lfloor \frac{n}{m} + \sqrt{2\frac{n}{m} \log n - \alpha_{0.5}} \right\rfloor\). As the median\(^12\) \(\nu\) of the Poisson distribution \(\text{Pois}(\frac{n}{m})\) is bounded by \(\frac{n}{m} - \log 2 \leq \nu < \frac{n}{m} + \frac{1}{5}\) \(^{10}\). Thus, \(\nu \approx \frac{n}{m}\), then

\[
K \approx \frac{n}{m} \Rightarrow \alpha_{0.5} \approx \sqrt{\frac{2n}{m} \log n}
\]  
(17)

Therefore the Corollary\(^1\) is proved.■

**Proof sketch of Corollary 2.** According to Pearson’s Skewness Coefficients\(^39\), the symmetry of a distribution is measured by its skewness. The probability distribution is approximately symmetrical to its mean when the skewness is small. According to \(^40\), the skewness of Poisson distribution \(\text{Pois}(\frac{n}{m})\) is \((-\frac{n}{m})^{-0.5}\). Thus when \(n \gg m \log m\) the \(\text{Pois}(\frac{n}{m})\) is approximately symmetrical to its mean \(\frac{n}{m}\).

Because when \(\alpha = 1\) the actual \(P_{\text{worst}}(m, n, \alpha)\) should be \(1\) \(\approx 0\) (because the large flow rate is the same as the legitimate flow rate, thus the detection equals to randomly picking one from \(m\) counters), thus the approximate lower bound \(1 - Q(K_{\alpha=1}, \frac{n}{m})\approx 0\), where \(K_{\alpha=1} = \left\lfloor \frac{n}{m} + \sqrt{\frac{2n}{m} \log n - 1} \right\rfloor\). As \(\text{Pois}(\frac{n}{m})\) is symmetrical to \(K_s = \frac{n}{m}\), when \(K = K_s + (K_s - K_{\alpha=1}) \approx \frac{n}{m} - \sqrt{\frac{2n}{m} \log n}\), the \(1 - Q(K, \frac{n}{m})\approx 1\), in which \(\alpha \approx 2\alpha_{0.5}\) (according to Corollary\(^1\)). Thus, \(\alpha_{1.0} = 2\alpha_{0.5}\) has been proved.■

### C.2 Proof Sketch For RLFD Total Detection Probability

**Proof sketch of Theorem\(^3\)**. For the detection level \(k\), we use \(A_{k,\alpha}\) to denote the event that the counter containing the large flow \(f_{atk}\) with average rate of \(R_{atk} = \alpha \gamma\) in the level \(k\) is selected for the next level, where \(\gamma\) is the threshold rate, \(\alpha > 1\). Then the total probability for RLFD to catch the large flow \(f_{atk}\) in one detection cycle is

\[12\] The \(K\) such that the CDF \(Q(K, \frac{n}{m}) = 0.5\)
\[ Pr(A_\alpha) = Pr(A_{1,\alpha}, A_{2,\alpha}, A_{3,\alpha}, ..., A_{d,\alpha}) \]
\[ = Pr(A_{1,\alpha}) \cdot Pr(A_{2,\alpha}|A_{1,\alpha}) \cdot Pr(A_{3,\alpha}|A_{2,\alpha}, A_{1,\alpha}) \]
\[ \quad \vdots \]
\[ = Pr(A_{d,\alpha}|A_{d-1,\alpha}, ..., A_{1,\alpha}) \]
\[ = Pr(A_{1,\alpha}) \cdot Pr(A_{2,\alpha}|A_{1,\alpha}) \cdot Pr(A_{3,\alpha}|A_{2,\alpha}) \]
\[ \quad \vdots \]
\[ = Pr(A_{d,\alpha}|A_{d-1,\alpha}) \]  
\[ (18) \]

As we described in Section 4.3, we use the Cuckoo hashing in the bottom level \( d \) to randomly assign flows into counters. Because we set enough levels to make the input flows in the bottom level less than the counters, the \( Pr(A_{d,\alpha}|A_{d-1,\alpha}) \approx 1 \). For the levels \( k < d \) with \( n^{(k)} \) legitimate flows, according to Theorem 2, the \( Pr(A_{k,\alpha}|A_{k-1,\alpha}) \geq P_{\text{worst}}(m, n^{(k)}, \alpha) \). Considering the maximum number of full-use legitimate flows in a link is \( n_\gamma = \rho/\gamma \),

- When \( n < n_\gamma \), \( Pr(A_{k,\alpha}|A_{k-1,\alpha}) \geq P_{\text{worst}}(m, n^{(k)}, \alpha) \)
- When \( n \geq n_\gamma \), \( Pr(A_{k,\alpha}|A_{k-1,\alpha}) \geq P_{\text{worst}}(m, n_\gamma, \alpha) \)

Therefore,

\[ Pr(A_\alpha) \geq \prod_{k=1}^{d-1} P_{\text{worst}}(m, \min(n_\gamma, n^{(k)}), \alpha) \]  
\[ (19) \]

, where we approximately let \( n^{(k)} = n/m^{k-1} \), which is the average value of \( n^{(k)} \) over repeated detection. \( n \) is the number of legitimate flows in the link.

According to Equation 19 and the fact that \( a_{1,0} \) decreases fast as the \( n^{(k)} \) decreases by the factor of \( m \), \( P_{\text{worst}}(m, n^{(k)}, \alpha) \) for \( n^{(k)} < n_\gamma \) does not affect the product much for the most of \( \alpha \) values. Therefore, we can approximate \( Pr_{\text{worst}}(A_\alpha) \) as follows:

\[ Pr(A_\alpha) \geq \left\{ \begin{array}{ll}
\prod_{\{k|n^{(k)} \geq n_\gamma\}} P_{\text{worst}}(m, n_\gamma, \alpha), & \text{when } n \geq n_\gamma \\
P_{\text{worst}}(m, n, \alpha), & \text{when } n < n_\gamma
\end{array} \right. \]  
\[ (20) \]

, where size of \( \{k|n^{(k)} \geq n_\gamma\} \) is \( \lceil \log_m(n/n_\gamma) \rceil + 1 \), because \( n^{(k)} = n^{(k-1)}/m \).

According to Theorem 2, approximately \( P_{\text{worst}}(m, n, \alpha) \geq 1-Q(K, \frac{n}{m}) \) where \( K = \left\lceil \frac{n}{m} + \sqrt{\frac{2n}{m} \log n - \alpha} \right\rceil \). Thus we can derive Theorem 3 from Equation 20.

### C.3 Proof Sketch For Twin-RLFD Theoretical Overuse Damage

The upper bound of the expected overuse damage can be derived from the average rate of a flat large flow and the expected detection delay: \( E(D_{\text{over}}) \leq E(T_{\text{delay}}) \cdot R_{\text{atk}} \), because attack flows cannot cause more overuse damage than the amount of traffic over-sent \( E(T_{\text{delay}}) \cdot R_{\text{atk}} \). For a bursty flow with duty cycle \( \theta \) and burst period \( T_b \), a RLFD can also treat it as a flat flow at the time of each burst interval \( \theta T_b \). Thus, we can still use the detection probability for flat flows to calculate the damage for bursty flows.

**Lemma 2** and proof sketch.
Lemma 2. A RLFD with detection cycle $T_c$ can detect bursty flows with $\theta T_b \geq 2T_c$ with the expected overuse damage:

$$E(D_{over}) \leq \begin{cases} 
T_c\gamma\alpha/\theta \left(1 - Q(K, \frac{n_{\gamma}}{m})\right)^{[\log_m(n/n_{\gamma})]+1}, & \text{when } n \geq n_{\gamma} \\
T_c\gamma\alpha/\theta \left(1 - Q(K, \frac{n}{m})\right), & \text{when } n < n_{\gamma} 
\end{cases}$$

(21)

where $K = \left\lfloor \frac{n_{\gamma}}{m} + \sqrt{2 \frac{n_{\gamma}}{m} \log n - \frac{\alpha}{\theta}} \right\rfloor$, $K = \left\lfloor \frac{n}{m} + \sqrt{2 \frac{n}{m} \log n - \frac{\alpha}{\theta}} \right\rfloor$, and $Q(x, \lambda)$ is the CDF of the Poisson distribution $\text{Pois}(\lambda)$.

Proof sketch: Because $\theta T_b \geq 2T_c$, thus for each burst period $T_b$ there must be at least $\left\lceil \frac{\theta T_b}{T_c} - 1 \right\rceil$ detection cycles, in which RLFD can see the attack traffic in all levels. When the RLFD observes the bursty flow, the only difference from the detection over flat flow is that, the traffic rate at that moment is $\frac{\alpha}{\theta}\gamma$, instead of $\alpha\gamma$ in the case of flat flows. Thus, the probability $\Pr(A_{\alpha})$ to detect such bursty flow in one detection cycle is calculated as the one for flat flow detection in Theorem 3, by replacing the $\alpha$ with the $\frac{\alpha}{\theta}$.

The expected detection delay $E(T_{delay})$ is derived as follows:

$$E(T_{delay}) \leq \frac{1}{\Pr(A_{\alpha})} \left\lceil \frac{T_b}{T_c} - 1 \right\rceil \approx \frac{T_c}{\theta \Pr(A_{\alpha})}$$

(22)

Then we get the over-sent attack traffic in the input link is $E(T_{delay}) \cdot R_{atk}$, and the overused bandwidth by attack traffic is less than or equal to that, because some attack packets may also be dropped during congestion. Thus we get the expected overuse damage $E(D_{over})$:

$$E(D_{over}) \leq E(T_{delay}) \cdot R_{atk} \leq T_c\gamma\alpha/\theta \Pr(A_{\alpha})$$

(23)

Thus, according to Theorem 3, we get the upper bound of the overuse damage in the Lemma 2. The proof also holds when $\theta = 1$, which is for the case of flat flows. 

Proof sketch of Theorem 4. The overuse damage in the case of $\theta T_b \geq 2T_c^{(1)}$ are from Lemma 2. When $\theta T_b < 2T_c^{(1)}$ and $R_{atk} < \theta \gamma_h$, we prove the damage as follows:

$$T_b < \frac{2T_c^{(1)}}{\theta} < \frac{2T_c^{(1)} \gamma_h}{R_{atk} \gamma_h} = \frac{2T_c^{(1)} \alpha \gamma_h}{\alpha \gamma_h} = \frac{T_c^{(2)}}{d}$$

(24)

Thus the $T_b$ is less than a detection level period of the $EFD^{(2)}$, which means the bursty flow is like a flat flow to $EFD^{(2)}$. Therefore, we use the overuse damage upper bound in Lemma 2 when $\theta = 1$, $T_c = T_c^{(2)}$, and we get

$$E(D_{over}) \leq \begin{cases} 
T_c^{(2)}\gamma\alpha/\left(1 - Q(K, \frac{n_{\gamma}}{m})\right)^{[\log_m(n/n_{\gamma})]+1}, & \text{when } n \geq n_{\gamma} \\
T_c^{(2)}\gamma\alpha/\left(1 - Q(K, \frac{n}{m})\right), & \text{when } n < n_{\gamma} 
\end{cases}$$

(25)
where \( K_\gamma = \left\lfloor \frac{n}{m} + \sqrt{\frac{2n}{m}} \log n - \alpha \right\rfloor, \) \( K = \left\lfloor \frac{n}{m} + \sqrt{\frac{2n}{m}} \log n - \alpha \right\rfloor. \) By replacing \( T_c^{(2)} \) with \( \frac{2m}{\alpha \gamma} T_c^{(1)} \), we proved the Theorem 2.

**D Additional Table**

| \( m \) | 20 | 40 | 70 | 100 | 150 | 200 | 400 |
|---|---|---|---|---|---|---|---|
| \( T_c^{(1)} \) | .242 | .242 | .242 | .242 | .242 | .242 | .242 |
| **Single RLFD** | | | | | | | |
| \( d \) | 4 | 3 | 3 | 3 | 3 | 3 | 2 |
| \( T_c^{(1)} \) | .968 | .726 | .726 | .726 | .726 | .726 | .484 |
| **Twin-RLFD (in CLEF)** | | | | | | | |
| \( d \) | 7 | 5 | 4 | 4 | 3 | 3 |
| \( T_c^{(1)} \) | 1.69 | 1.21 | .968 | .968 | .968 | .726 | .726 |
| \( T_c^{(2)} \) | 168.6 | 63.75 | 31.92 | 26.56 | 21.96 | 10.68 | 7.59 |

* Time unit is second.