

Latency- and Bandwidth-Minimizing Optimal Failure Detectors

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Abstract

Failure detectors are fundamental building blocks in distributed systems. *Multi-node failure detectors*, where the detector is tasked with monitoring N other nodes, play a critical role in overlay networks and peer-to-peer systems. In such networks, failures need to be detected quickly and with low overhead. Achieving these properties simultaneously poses a difficult tradeoff between detection latency and resource consumption.

In this paper, we examine this central tradeoff, formalize it as an optimization problem and analytically derive the optimal closed form formulas for multi-node failure detectors. We provide two variants of the optimal solution for optimality metrics appropriate for two different deployment scenarios. The *latency-minimizing* failure detector (LM-OFD) achieves the lowest average failure detection latency given a fixed bandwidth constraint for system maintenance. The *bandwidth-minimizing* failure detector (BM-OFD) will meet a desired detection latency target with the least amount of bandwidth consumed. We evaluate our optimal results with node lifetimes chosen from bimodal and power-law distributions, as well as real-world trace data from PlanetLab hosts that spans five months. Compared to standard failure detectors in wide use, our approach reduces failure detection latencies by 40% on average for the same bandwidth consumption, or conversely, reduce the amount of bandwidth consumed by 30% for the same failure detection latency.

Keywords: Failure detection, overlays, wide-area networks.

1 Introduction

Detecting failed nodes is an essential task in many distributed systems. In particular, *multi-node failure detectors* are ubiquitous in many settings and form a fundamental part of higher-level failure recovery operations in many systems. Specifically, a multi-node failure detector is tasked with monitoring a set of nodes (a *fail-detect set*) and needs to detect failures within the set with low latency while consuming little network bandwidth. Multi-node failure detectors are fundamental components in overlays, content distribution networks, and group communication services, as well as many other distributed systems. For instance, peers in a distributed hash table need to monitor nodes in their routing tables to detect when they should replace or take over the duties of failed neighbors. A content distribution network needs to monitor the status of servers in order to direct clients to the most suitable live replica. Group communication systems [3, 15, 23, 20] use failure detectors to determine group membership. Much past work on distributed failure detectors [7, 9, 22, 1, 21, 2, 5, 32, 13, 27, 18, 36, 12] assumes and builds on top of such a failure detector module at each node.

The challenge in failure detection stems from the conflicting goals of low detection latency and low bandwidth consumption. In the limit, low latency can be achieved by using all available bandwidth to constantly poll the nodes in the fail-detect set. Similarly, it is possible to build a very low bandwidth (and infinite latency) failure detector by not probing any nodes at all, though such a detector is useless in practice. Between these two extremes, there exists an optimal point where a node checks members of its fail-detect set at just the right frequency such that the total bandwidth consumption is limited to a targeted value and failure detection latency achieves a desired level of performance. This paper presents a technique for determining this optimal point.

The standard practice in distributed systems is to use ad hoc measures to pick a single period τ , and to probe every node in the fail-detect set every τ seconds [29, 28, 16, 17]. The selection of a single global τ would make sense in a setting where all nodes are homogeneous and exhibit the same session duration. However, past studies have demonstrated that node lifetimes are highly skewed [30], which in turn renders a single probe frequency far from optimal. It is possible to posit many heuristics for picking a node specific τ_i , but heuristics are unlikely to achieve a good tradeoff between bandwidth and latency, and the conditions under which they might work well are hard to characterize. In this paper, we derive the optimal strategy for

resource-optimal failure detection from first principles.

Overall, this paper makes three contributions. First, it formalizes the multi-node failure detection problem, formulates it in a manner amenable to mathematical optimization and identifies two variants of the optimal solution encountered in practice. The *latency-minimizing* variant minimizes failure detection latency while constraining the amount of bandwidth used for probing nodes. The *bandwidth-minimizing* variant achieves a targeted failure detection latency while minimizing the amount of bandwidth consumed. The former is applicable when the amount of bandwidth dedicated to system overhead is known a priori as it can achieve the optimal latency within a strict resource limit, while the latter is best suited for settings where a particular performance level is sought from the failure detector module as it can achieve the performance goals using the minimal resources required. Second, this paper analytically derives closed-form formulas for the optimal rate at which failure checks need to be performed to solve the latency- and bandwidth-minimizing failure detection problems. The closed form formulas depend solely on parameters readily available in the problem statement or measurable via simple mechanisms, such as the distribution of node lifetimes, loss rate, targeted level of accuracy, the bandwidth constraint and the latency target. Finally, we evaluate the proposed solutions using five months of measurement data from PlanetLab, compare them to standard failure detectors commonly found in distributed systems, and show that they significantly improve the performance metrics. Compared to the the failure detectors found in FreePastry and Bamboo implementations, LM-OFD improves failure detection latency by 40% while consuming the same amount of bandwidth as the standard solution, while BM-OFD can reduce bandwidth requirements by 30% for typical failure detection latency targets.

The next section provides a brief overview of related work in failure detection. Section 3 describes our approach and derives the formulas for an optimal failure detector. Section 4 describes our implementation and discusses some of the problems encountered in failure detection in practice. Section 5 evaluates our approach using detailed, long-term data from 561 PlanetLab hosts. Section 6 summarizes our contributions and describes future directions.

2 Related Work

Past work on failure detectors has focused on the *single-node* and *distributed* failure detection problems, which differ substantially from the multi-node failure detection problem we examine. Our work involves

different tradeoffs from the former and is complementary to the latter. It arose in the context of peer-to-peer systems, where failure detection is critical, and existing approaches are typically ad hoc.

Chen [8] provides the most comprehensive analysis to date of the quality of service (QoS) guarantees for single-node failure detectors. Given QoS requirements, Chen et al. [9] show how to compute the parameters, in particular the time between heartbeats and estimated network delays, for failure detectors under probabilistic message losses and network delays. Bertier et al. [4] propose an adaptive failure detector that computes the heartbeat period by combining the TCP estimation function with Chen's, while [14] automatically adjusts the heartbeat period based on network characteristics. These approaches examine a single node at a time; they treat a set of nodes being monitored as collection of independent single-node detectors and do not examine the resource tradeoffs between different hosts. In contrast, we specifically focus on multi-node failure detectors and show how to optimally dedicate bandwidth among multiple nodes in the fail-detect set.

Some past work has examined how to incorporate application specific requirements into failure detectors. In [10], the authors use two different timeouts to generate two levels of suspicions. Instead of using a suspect list, φ and Φ failure detectors [19, 11] compute an estimate for each node that captures the likelihood that the node has crashed. This approach provides a more expressive interface from the failure detector to applications. In contrast, we provide a richer interface to the failure detector by which applications can specify their performance goals and resource constraints, and achieve those goals within the constraints.

Recent work has examined how to adaptively calculate a homogeneous probing period for peers in an overlay network [6]. The authors derive an analytical model to compute the probing rate given packet loss rates and node lifetimes. The protocol is able to self-tune the probing rate in response to changes in these two parameters. In contrast, we derive an analytical model to compute a node-specific polling rate for each node as opposed to a single, homogeneous probing rate for all nodes, and achieve analytical, closed form solutions for the optimal strategy.

Distributed failure detectors combine suspicions from multiple nodes into an accurate estimate on process status. Chandra and Toueg [7] introduce the concept of unreliable distributed failure detectors and characterize them in terms of completeness and accuracy. They use the failure detector abstraction to solve the consensus and atomic broadcast problems in an asynchronous network model. This approach has formed the foundation of much subsequent work on reducing message complexity and network load [22, 1, 21, 2].

Subsequent work in distributed failure detectors has focused on how to detect failures in a set of servers

in a scalable manner as the size of the set grows. Hierarchical failure detectors [5, 32] arrange nodes into a multi-level hierarchy which partitions the monitoring and reporting tasks along a tree to improve scalability. Gulfstream [13] reduces probing traffic by arranging nodes in a circular virtual identifier space and probing only adjacent nodes. Gossip-based failure detectors [27] can improve scalability and reduce failure detection time via random and periodic communication among the monitoring nodes. Recent work by Gupta et al. [18] presents a randomized distributed failure detector that achieves low failure detection latency. A recent study on failure detection in overlay networks [36] empirically examines the performance of five distributed failure detection algorithms, including the basic periodic failure detector that we use for our baseline. FUSE [12] is a distributed failure detector that focuses on lightweight and scalable failure notification. These systems assume the presence of a multi-node failure detector on each node, and focus on the communication among the monitoring nodes. Our approach is complementary to these systems.

3 Approach

In this section, we first describe the general system model we use as our foundation, then analytically express the tradeoffs involved in failure detection, and finally derive the equations for two variants of an optimal failure detector.

3.1 System Model

The key metrics of interest in a multi-node failure detector are failure detection latency, bandwidth overhead and accuracy. We assume that each node j has a fail-detect set σ_j , $|\sigma_j| = N$, which it needs to monitor for failures. We build on an end-to-end model, in which the preferred way to test if a node has failed is to send an application-specific request and receive a response. Typically, such a request consists of a no-op remote procedure call handled at the application level, though a simpler substitute, such as an ICMP ping packet, may be used in cases where the application shares its fate with the entity responding to the request. We use the term *ping* for a single such packet sent to detect node failure; a *probe* is a series of up to r pings that are separated by a Δ timeout value, sent in sequence to guard against losses in the network.

The current state of the art in failure detection is to pick a fixed period τ and to probe every node $i, i \in \sigma_j$ every τ seconds. If consumed bandwidth is not a concern, low failure detection latencies can be achieved simply by setting $\tau = 0$ and continuously probing every node. This strategy is clearly a terrible choice in

Parameter	Description
τ_i	Probing period for node i in the fail-detect set
N	Number of nodes in the fail-detect set
L	Failure detection latency
T_L	Targeted failure detection latency
B	Bandwidth consumed for failure detection
T_B	Targeted bandwidth consumption
l_i	Estimated lifetime for node i
d_i	Mean time to recovery for node i
α	Desired failure detection accuracy
p	Round-trip packet loss probability
Δ	Timeout for a ping response
r	Maximum number of ping packets in a probe
q	Expected number of ping packets in a probe
s	Ping packet size

Table 1: **Notation.** Key variables used in the analysis.

practice, as all available bandwidth would be dedicated to failure detection, leaving no surplus bandwidth for useful work. We therefore limit the maximum per-node bandwidth the system can dedicate to failure detection to T_B ¹.

A node j probes a node i in its fail-detect set, $\sigma_j, i \in \sigma_j$ with period $\tau_i, \tau_i > r\Delta$, where Δ is the ping timeout period. If any ping elicits a response, the probe is successful, the series of pings are terminated, and the node is deemed alive. If more than r consecutive pings to a given node elicit no response, the destination node is marked as having failed.

Table 1 summarizes all the variables used in the following analysis. A key variable in the analysis is the estimated lifetime for a given node, which is denoted by l_i . Given these key variables, the next section derives the relevant formulas for optimal failure detection.

3.2 Latency-Minimizing Failure Detector

First, we examine a failure detector designed to achieve the lowest possible failure detection latency while remaining within a given bandwidth budget.

Failure detection latency is the time between the time a given target node failed, either due to network or node failure, and the time the detector decides that the node failed. If the probing period is τ_i and a node is considered to be down after a probe is unsuccessful, then the average failure detection latency is $\frac{\tau_i}{2}$.

Consider the behavior of the system over a long time period κ . For each neighbor i , a node will use

¹We assume a uniform T_B for all nodes in the system for simplicity of discussion; it is straightforward to extend the analysis to accommodate a node-specific bandwidth cap.

bandwidth $\frac{s}{\tau_i}$ to send out a probe every probing interval. Therefore, the total amount of network bandwidth consumed at each node for monitoring the fail-detect set over the period κ is

$$B = \sum_{i=1}^N \frac{sq}{\tau_i} \quad (1)$$

In the equation above, s is the size of the ping packet, and q is the expected number of ping packets in a probe before the probe either successfully elicits a response or is unsuccessful. The precise definition of q depends on the operating environment, and is derived in Section 3.6. For now, note that it is a constant between 1 and r ; 1 if node i is continuously up and there are no network losses, and r if the node is permanently down.

From the lifetime estimate of a node, we can calculate the expected number failures of that node over time κ , which is $\frac{\kappa}{l_i}$. Average latency of detecting failed neighbor i is $\frac{\tau_i}{2} + r\Delta$. Consequently, the average latency of detecting failed neighbors over time κ is given by:

$$L = \frac{\sum_{i=1}^N (\frac{\tau_i}{2} + r\Delta) \times \frac{\kappa}{l_i}}{\sum_{i=1}^N \frac{\kappa}{l_i}} \quad (2)$$

We can now cast the latency-minimizing failure detection problem as a mathematical optimization problem: minimize average latency of detecting failed neighbors (Eq. 2) subject to bandwidth constraint $B \leq T_B$ (Eq. 1). We introduce Lagrange multiplier λ , and use the independence of the terms under the summation to yield the following equation.

$$\frac{1}{2l_i} = -\lambda \frac{sq}{\tau_i^2}, \forall i, 1 \leq i \leq N \quad (3)$$

Given this equation, we can solve for τ_i using the constraint $B \leq T_B$ to reach the following solution:

$$\tau_i^* = \frac{sq}{T_B} \sqrt{l_i} \left(\sum_{j=1}^N \frac{1}{\sqrt{l_j}} \right), \forall i, 1 \leq i \leq N \quad (4)$$

A simple example illustrates the potential benefits of this approach. Suppose that a system consists of 40 nodes whose lifetimes are drawn from a bimodal distribution. Twenty short-lived hosts have lifetimes of 1 hour, while the other 20 long-lived hosts have lifetimes of 225 hours. Suppose that the amount of bandwidth

devoted to failure detection is 1 kB/sec, and that the size of a ping packet is 100 bytes. The traditional approach to failure detection would ping both the long and short-lived node every 4 seconds, consuming 1kB/sec and yielding an average failure detection latency of 2 seconds. Our latency-minimizing optimal failure detector (LM-OFD) algorithm instead pings long- and short-lived nodes every 32 and 2.13 seconds respectively, consumes 1 kB/sec, and achieves an average failure detection latency of 1.2 seconds.

3.3 Bandwidth-Minimizing Failure Detector

In some deployment scenarios, the amount of bandwidth dedicated to system maintenance is not capped, and the critical performance metric for the failure detector is the average detection latency. Next, we examine a failure detector designed to achieve a targeted failure detection latency, while minimizing the bandwidth consumed to achieve the desired level of performance.

The derivation of the parameters for a bandwidth-minimizing failure detector is similar to the latency-minimizing failure detector, except that the mathematical optimization problem is slightly different. Namely, BM-OFD will minimize bandwidth (Eq. 1) given a target failure detection latency (Eq. 2) of T_L . We introduce Lagrange multipliers to find the minima and solve for the optimal τ_i subject to the constraint $L \leq T_L$, similar to the approach in the previous subsection. This yields the following equation.

$$-\frac{sq}{\tau_i^2} = \lambda \left(\frac{1}{2l_i \sum_{j=1}^N \frac{1}{l_j}} \right) \quad (5)$$

Now, we can solve for τ_i using Equation 2, the constraint $L \leq T_L$ and Equation 5 to reach the following solution.

$$\tau_i^* = \frac{2(T_L - r\Delta)(\sum_{j=1}^N \frac{1}{l_j})\sqrt{l_i}}{\sum_{j=1}^N \frac{1}{\sqrt{l_j}}}, \forall i, 1 \leq i \leq N \quad (6)$$

We can illustrate the potential benefits of this approach with a simple example. Assuming the same sample setup as in the preceding section, a traditional, periodic failure detector that targets 2 second average failure detection latency would ping nodes every 4 seconds, and consume 1 kB/sec as a consequence. Our BM-OFD result instead pings long- and short-lived nodes every 56.5 and 3.77 seconds respectively, achieves 2 second failure detection latency on average, and consumes only 0.56 kB/sec.

3.4 Worst-case guarantees

Our derivation so far targeted a minimal or desired detection latency in the average case. The approach described above does not (yet) provide a bound on worst-case detection latency. Such a bound can be accommodated by specifying the worst-case detection latency, Γ , solving for τ_i^* using the LM-OFD or the BM-OFD equations above, and setting τ_i to Γ in cases where $\tau_i^* \geq \Gamma$. Subtracting the resulting bandwidth consumption from B and re-solving for the remaining τ_j will yield the optimal solution for the average-case behavior subject to the worst-case bound.

3.5 Probe length

Accuracy of failure detection depends significantly on transient losses encountered in the network. Since network failures are indistinguishable from host failures, losses in the network can lead to false positives where a node erroneously concludes that another node is down because all pings or ping responses were lost in the network. We consider a ping lost if a response is not received within a timeout period Δ . Previous work on temporal dependence of packet losses [35] indicates that for choices of $\Delta > 1s$, the losses are likely to be independent, yielding a probability of p^r for losing r consecutive ping packets, where p is the packet loss rate. In order to achieve a false positive rate at α , $0 \leq \alpha \leq 1$, we can pick $r = \log_p(1 - \alpha)$, and send r such consecutive pings after timeouts before declaring a node down.

3.6 Expected number of pings

Having derived analytical formulas for the optimal probing strategy, we are now in a position to compute q , the number of times a node expects to send ping packets to a monitored node before it successfully receives a response or concludes that the node is down. If the node is down, the expected number of pings is simply $q_i^{down} = r$. If the host is up, and the probability of loss of the ping-response pair is p , the expected number of ping packets is the sum of the number of pings for successfully receiving a response and declaring the node up (the summation term), and the number of packets for the remaining case where all packets are lost in the network and the node is erroneously declared down:

$$q_i^{up} = \left(\sum_{t=1}^r t p^{t-1} (1-p) \right) + r p^r = \frac{1-p^r}{1-p} \quad (7)$$

The precise value for q depends on the manner in which the failure detector is used. Failure detectors can

be classified into two categories based on how they manage their fail-detect sets. In *static* fail-detect sets, the set of nodes being monitored does not change in response to failures. Static fail-detect sets are encountered in practice in settings where the system is closed and set members are known a-priori; for instance, replicated DNS servers running BIND monitor the server set without replacement through failures. In *dynamic* fail-detect sets, failed nodes in the fail-detect set are removed at run-time. They may potentially be replaced with alternative nodes, but nevertheless the invariant is that the fail-detect set consists of all live nodes at all times. Dynamic fail-detect sets are encountered in settings where system membership can change at run time and newly arriving nodes can be tasked with explicitly announcing their arrival. For instance, the Pastry overlay replaces failed nodes in a node’s vicinity (leaf-set) by picking the closest alive nodes in the circular identifier space. In effect, failure detectors are generic event detectors; static fail-detect sets correspond to event detectors that monitor both failure and recovery events, whereas dynamic fail-detect sets correspond to event detectors that monitor only failures.

In a dynamic fail-detect set, failed nodes are probed at most once following a failure. Consequently, $q = \text{avg}(q_i^{up})$. In a static fail-detect set, nodes are probed even when they are down. We need consider not only the lifetime, but also d_i , the mean time to recovery, in order to model q accurately. Taking into account the percentage of time a node is up or down, and the relative costs of probing alive and failed nodes leads to the following formula:

$$q = \sum_{i=1}^N \left(\frac{d_i}{l_i + d_i} q_i^{down} + \frac{l_i}{l_i + d_i} q_i^{up} \right) \quad (8)$$

This completes the full derivation of all parameters required for the latency- and bandwidth-minimizing optimal failure detectors from first principles. The critical inputs to the formulas are the estimates for node lifetimes, whose accuracy greatly determines the performance of the failure detector. The next section examines the lifetime estimates as well as other practical considerations in implementing and OFD.

4 Implementation

In order to actually build an optimal detector, the parameters used in the analysis need to be accurately and efficiently estimated so the formula can be computed. The key parameter a practical implementation needs to estimate is l_i , a node’s lifetime.

The choice of an estimation technique depends on the distribution of node lifetimes (also known as session lengths) as well as their variation over time. Note that for the defunct case where node lifetimes are homogeneous, i.e. identical for all nodes, our optimal solution yields the same result as traditional, periodic failure detectors. In practice, studies have shown that node lifetimes vary substantially, which provides the opportunity for our approach to significantly outperform simple periodic polling.

We examine three simple techniques for estimating node lifetimes, a moving average, an exponential moving average, and a hybrid approach. A node monitoring other nodes' failures has ready access to the node's last session length. In Moving Average (MovAvg), the monitoring node will calculate the average lifetime of last k sessions, and use it for its estimated value of l_i . In Exponential Moving Average (ExpAvg), a node estimates the average lifetime l_i after the t^{th} session using the estimated lifetime l_i^{t-1} and the duration of the last session λ_i^t according to $l_i = (1 - \beta)l_i^{t-1} + \beta\lambda_i^t$. When β is large, the exponential average weights recent session durations more heavily than previous sessions.

Our Hybrid approach is driven by the observation, from PlanetLab data, that nodes tend to alternate between periods of frequent activity, followed by long quiescent periods of either being up or down. We capture this behavior with a bimodal moving average, which uses a "low" moving average table for sessions below a certain threshold κ and a "high" moving average table for the rest. When the current session length is below κ , we use the estimate from the "low" moving average. Otherwise, we use the estimate from the "high" moving average. The constant κ is set to 24 hours in our implementation, and the low and high tables are updated in response to failures, as well as when a monitored node's current session length exceeds the current lifetime estimate.

In our implementation, each node calculates the probing period for the nodes in its fail-detect set using the previously derived formulas, informed by estimates of node lifetime. The node lifetime estimates are computed using the Hybrid approach; we later provide a comparison of all three estimators and find empirically that it achieves the best results for the actual temporal variations in the PlanetLab data set. When a fresh new node is added, its lifetime estimate can be computed by querying the node (which will omit network failures but capture node uptime up to that point in time), by querying other nodes for their estimates (which assumes that the network characteristics are similar from different vantage points), or by simply assuming a representative default value, such as the average session duration for all nodes. The selection depends on the deployment scenario; in settings with moderate to high node churn, the initial estimate does

not materially impact performance.

The polling frequency for each node needs to be recomputed whenever inputs change significantly. Our implementation recomputes the polling frequency for each node reactively, whenever the fail-detect set is modified in response to node joins or failures, as well as proactively, every $\Omega = 5$ minutes.

Note that, while our optimal solution caps the amount of bandwidth stemming from failure detection actively performed by a given host, it does not take into account the bandwidth that the same node consumes when responding to pings initiated by other hosts. This simplification is intentional, since neighbor management algorithms in structured peer-to-peer systems typically provide (and themselves rely on) in-degree balancing, which ensures that the incoming load due to pings will not be concentrated at any one node and can be derived easily. An OFD implementation for an unstructured peer-to-peer system may need to pay attention to node in-degree imbalance if the overlay does not already guarantee in-degree balancing [34].

While failure detectors are typically designed as stand-alone modules independent from the applications they serve, an implementation can save bandwidth through a tighter integration between the detector and higher-level system functionality. In particular, aggressively harvesting information on node failures from higher levels can enable the detector to delay or skip probes, saving bandwidth. A typical OFD implementation will keep a countdown timer associated with each node it is monitoring, set initially to τ_i for that host. When an indication is received that the target node is up, for instance, via an application-level invocation to or from the target node, or via a probe in the reverse direction from the target back to the monitoring node, the timer can be reset to τ_i . Hence a busy overlay can piggyback failure detection onto naturally occurring traffic. Since the bandwidth savings possible with this optimization are highly application-specific, we ignore this optimization in our evaluation.

5 Evaluation

In this section, we evaluate the efficacy of our optimal failure detector using long-term uptime measurements collected on PlanetLab. We examine two metrics of importance, failure detection latency and bandwidth consumption. We compare our approach to common failure detection mechanisms deployed in real systems.

We compare our LM-OFD and BM-OFD failure detectors to the reference failure detector implementations used in FreePastry and Bamboo, two widely deployed distributed systems. In FreePastry (Version 1.3.2), each node periodically probes all nodes in its fail-detect set with a default period of 60 seconds. The

node is marked as down when a ping packet is lost. In Bamboo (version 20050701), each node periodically pings all nodes in its fail-detect set every 20 seconds. An initial ping failure within 20 seconds marks the node as “suspect,” which is followed immediately by a second ping with a 60-second timeout. A subsequent failure marks the node as having failed. Since the Pastry and Bamboo failure detectors use different probing schemes, they achieve different accuracies. We consequently adjust our algorithms to match the accuracy achieved by Pastry and Bamboo for a fair comparison.

We quantify the benefits of the LM-OFD and BM-OFD algorithms under three different lifetime distributions, two synthetic and one based on long-term traces from PlanetLab. We first examine a *bimodal* lifetime distribution, where nodes are either long- or short-lived. Such a scenario might be encountered in a system where there is a mix of client- and server-class nodes, such as a peer-to-peer system with super-peers. We pick a bimodal distribution with peaks at 30 and 300 minutes. We also examine a *Zipf* lifetime distribution, where the lifetime of a node is proportional to $1/i^\gamma$, where i is the longevity rank of the node and γ is 0.9; the node lifetimes range from 2 hours to 10 days. While these parameters are loosely inspired by [30], we present results from the synthetic bimodal and Zipf lifetime distributions to provide insight into the operation of the optimal solution by showing the types of gains possible in two well-characterized settings.

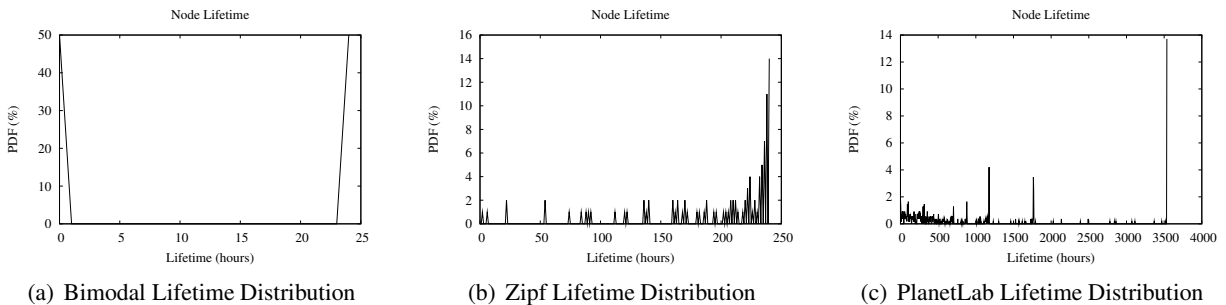


Figure 1: Lifetime distributions for the synthetic and real traces.

For a realistic evaluation, we examine the actual lifetime distribution collected via a long-running all-pairs ping measurement study over 561 nodes [33]. We examine 5 months of all pairs ping data collected between June 1 and October 26, 2005. The data contains the result of 10 consecutive pings from each node to all other nodes, sent every 15 minutes. Using the raw all pairs data, we establish a “ground truth” about the liveness of each node at each time interval. The start and end of a failure is randomized within the 15

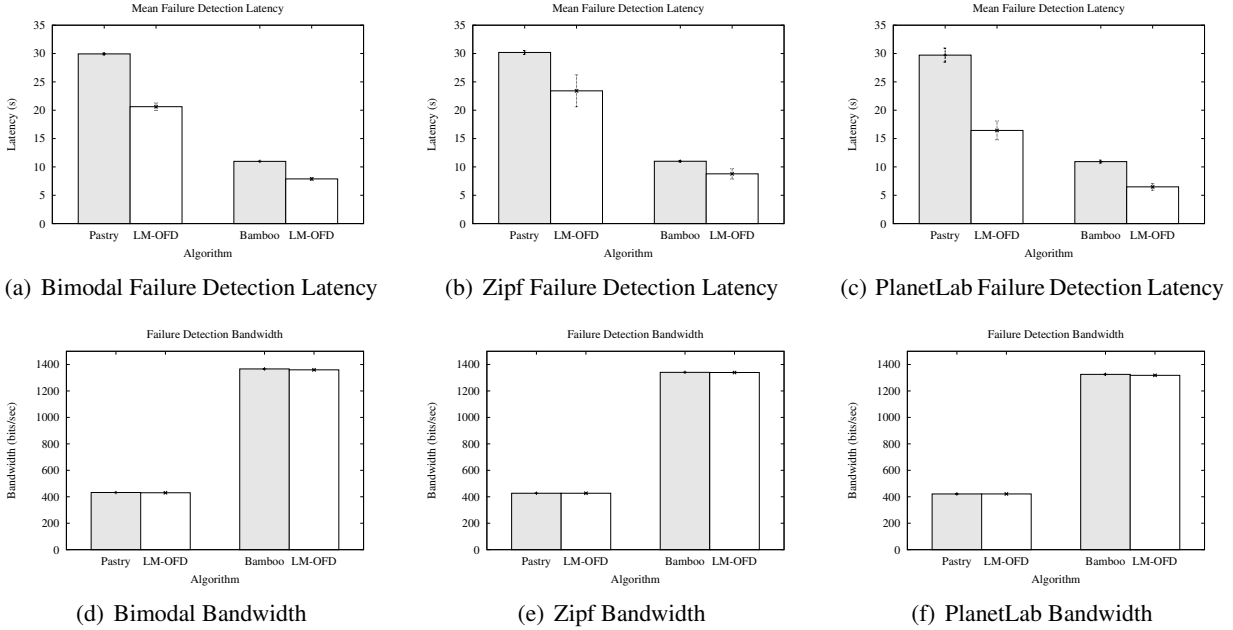


Figure 2: The performance of the latency-minimizing optimal failure detector.

minute bucket in which it is detected. While the 15 minute polling period may have missed failures with very short durations (as will data collected using any practical method based on polling), the PlanetLab data represents the most extensive and realistic public uptime data available on a geographically distributed system, and the slight bias away from failures with very short durations affects periodic failure detectors and OFD equally. Figure 1 shows the distribution of node lifetimes for the synthetic distributions and the PlanetLab traces.

Our simulations accurately reflect the costs and latencies of failure detection. We select fail-detect set size N to be 50, and take the size of a ping packet s to be 64 bytes. Nodes keep track of their own session durations and provide an initial estimate to other nodes when they initially join the network; subsequently, failure detectors perform their own measurements and estimates. We examined network loss rates p ranging from 0 to 0.05 [24] and found that loss rates in this range impact the results by less than a few percent. Consequently, we report only the conservative and realistic results from the 0.05 loss rate experiments. All reported measurements represent the average of 9 runs; bars indicate standard deviation for normally distributed data.

We first examine the central tradeoff between bandwidth consumption and achieved failure detection

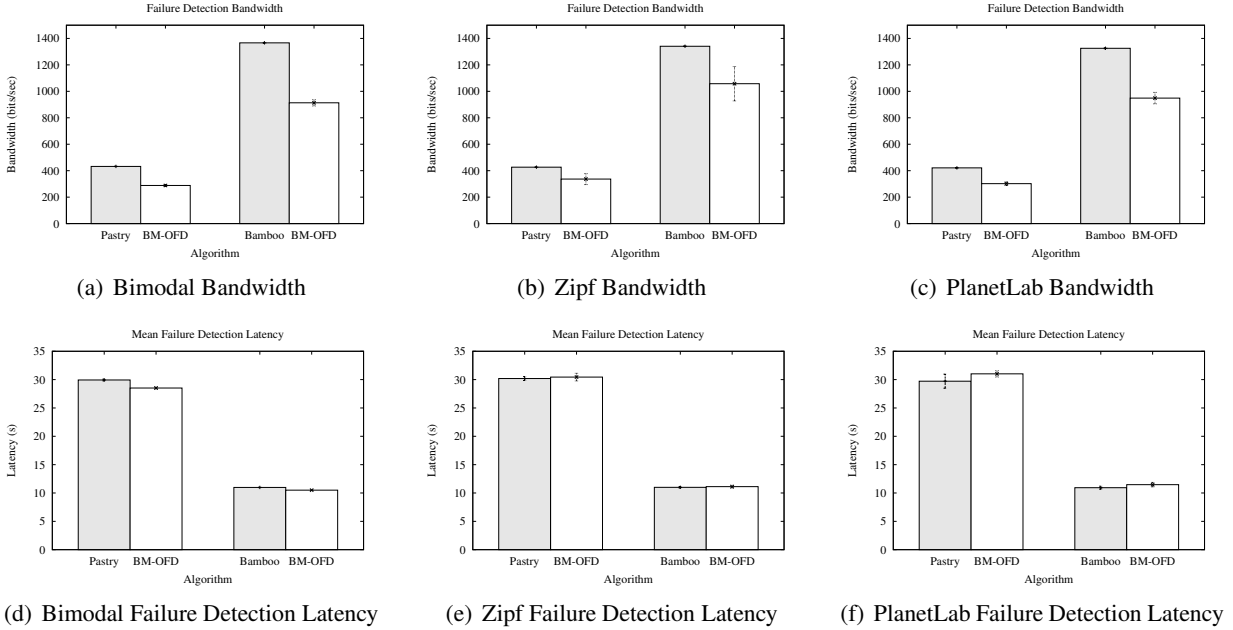


Figure 3: The performance of the bandwidth-minimizing optimal failure detector.

latency for latency-minimizing optimal failure detector (LM-OFD) at two different accuracy levels, and compare them to Pastry and Bamboo under three different lifetime distributions. Figure 2 compares the average failure latency achieved by LM-OFD to that of traditional, periodic failure detectors. LM-OFD achieves a 40% improvement in update latency for the real-world PlanetLab data. This significantly exceeds the improvement LM-OFD provides when node lifetimes are bimodal (32%) or Zipf (20%), partly because the PlanetLab nodes exhibit highly skewed session times. LM-OFD consumes approximately the same amount of bandwidth as Pastry and Bamboo while achieving significantly better detection latencies. This is not surprising, as our solution was crafted to take the desired bandwidth consumption as a constraint.

Next, we examine the bandwidth consumption and achieved failure detection latency for BM-OFD, parameterized to match the average latency of Pastry and Bamboo. Figure 3 shows that our bandwidth-minimizing failure detector consumes approximately 30% less bandwidth for the measured PlanetLab data, while approximately matching the average failure detection latency.

We next evaluate what kind of a strategy to use for estimating node lifetimes in a realistic LM-OFD implementation. We examine moving average (MovAvg), exponential moving average (ExpAvg), and the hybrid approach (Hybrid). To provide a point of comparison, we also examine a lifetime estimator, called

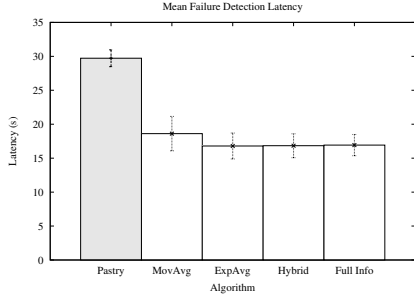


Figure 4: Failure detection latency using different lifetime estimators.

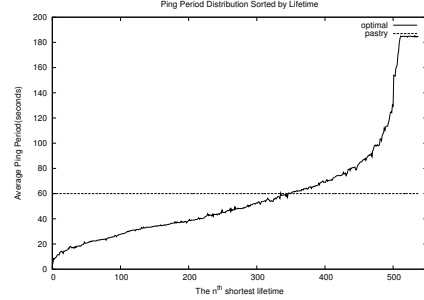
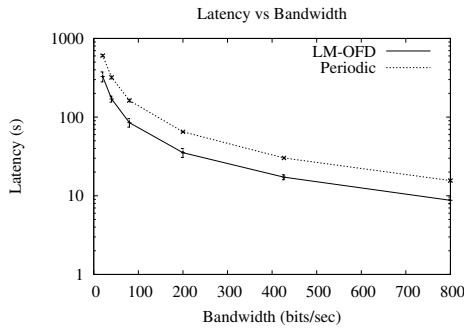


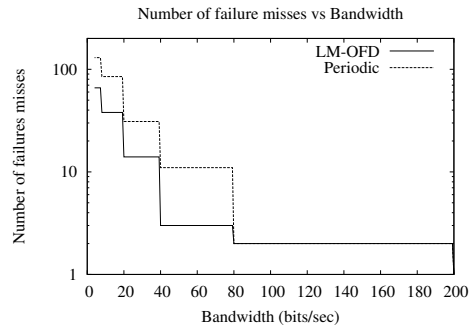
Figure 5: Average ping period sorted by lifetime, as computed by LM-OFD.

FullInfo, that has access to the full 5-month duration of the trace, and uses $l_i = \bar{l}$, the average of all session durations as its estimate. Note that such a failure detector is unrealistic, as it has access to future session lengths, and implicitly assumes that session lifetimes are distributed normally, but nevertheless provides a yardstick for the performance of other lifetime estimators. We examine exponential moving average with $\alpha = 0.75$; the size of the moving average windows for MovAvg and Hybrid are set to 3. Figure 4 shows that the Hybrid and ExpAvg estimators achieve results that are within a few percent of FullInfo.

Figure 5 provides insights into the operation of LM-OFD by plotting the average ping period $\bar{\tau}_i$ for each of the nodes sorted by average lifetime. LM-OFD preferentially pings the nodes with shorter lifetimes more often, dedicating the required bandwidth to quickly detect failures, while Pastry’s periodic failure detector pings every node with the same ping period. The probe period ranges from 3.4 seconds for the node with an average lifetime of 15 minutes to 3 minutes for the node with 3537 hours average lifetime.



(a) Bandwidth Vs Latency



(b) Bandwidth Vs Missed Failures

Figure 6: Failure detection latency and accuracy as a function of bandwidth for the PlanetLab trace.

Finally, we examine the behavior of LM-OFD as a function of the available bandwidth. Figure 6a

shows that LM-OFD achieves an average of 40% improvement in failure detection latency under bandwidth constraints ranging from 0.5 bytes/s to 800 bytes/s. Note that the choice of τ_i may impact the accuracy of the failure detector if the node fails and recovers between successive probes. Figure 6b shows the number of missed failures under different bandwidth limits. With an extremely tight bandwidth limit of 1 byte/s, the periodic failure detector misses 85 failures while LM-OFD only misses 38, and LM-OFD achieves much better accuracy across a range of bandwidths, mostly because it concentrates its polling activity on nodes likely to fail. While this experimentally confirmed behavior is encouraging, missed failures are not a significant issue in settings with modest amounts of bandwidth dedicated to monitoring. In the PlanetLab trace, neither periodic nor LM-OFD miss any failures when bandwidth used for failure detection exceeds 0.2 Kbits/sec,

Overall, OFD failure detectors utilize the critical resource, bandwidth, optimally, achieving significant improvements in detection time for a targeted bandwidth or savings in overhead for a targeted latency compared to traditional periodic failure detectors.

6 Conclusions

In this paper, we examined the problem of how to allocate bandwidth to monitoring nodes in a multi-node failure detector. We formalized the problem, expressed it analytically in a form tractable for mathematical optimization, and derived closed-form solutions. We developed solutions to two variants of the problem, suitable for two different settings: our *latency-minimizing* failure detector achieves the lowest failure detection latency on average given a bandwidth constraint, while our *bandwidth-minimizing* failure detector meets a targeted detection latency using the least amount of bandwidth necessary to reach that goal. Evaluation of our approach using real-world trace data spanning five months from PlanetLab hosts indicates that the approach is effective. Compared to traditional failure detectors, our optimal approach can reduce detection latencies by 40% while using the same amount of bandwidth, or reduce bandwidth consumed by 30% for a target detection latency.

Overall, the proposed approach lends itself to a straightforward implementation, is complementary to decades of work in distributed failure detectors, and is suitable for recently emerging peer-to-peer systems. We are currently in the process of building a parameterizable failure detector toolkit based on OFD and integrating it into our peer-to-peer systems [26, 25, 31]. We hope that such a toolkit will lead to a more

principled, less ad hoc implementations of failure detectors among distributed system practitioners.

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