Chapter 3: Efficient Implementation of Fair Queueing

3.1. Introduction

The performance of packet switched data networks is greatly influenced by the queue service discipline in routers and switches. While most current implementations are of the first-come-first-served discipline, Chapter 2 shows that the Fair Queueing (FQ) discipline provides better performance. Thus, there has been considerable interest in studying the theoretical and practical aspects of the algorithm [50, 57, 89, 93, 125, 126].

Chapter 2 discussed the properties of Fair Queueing; however, no particular implementation strategy was suggested. If future networks are to implement the discipline, it is necessary to study efficient implementation strategies. Thus, this chapter examines data structures and algorithms for the efficient implementation of Fair Queueing.

We begin by summarizing the Fair Queueing Algorithm. After pointing out its three components, we study the efficient implementation of each component. The component that critically affects the performance is a bounded size priority queue. In the rest of the chapter, we develop a technique to study average case performance of data structures, and use it to compare several priority queue implementations. Our results indicate that cheap and efficient implementations of Fair Queueing are possible. Specifically, if packet loss can be avoided, an ordered linked list implements a bounded size priority queue simply and efficiently. If losses can occur, then explicit per-conversation queues provide excellent performance.

3.2. The Fair Queueing algorithm

Let the ith packet from conversation α, of size P_i^α, arrive at a switch at time t. Let F^α denote the largest finish number for any packet that has ever been queued for conversation α at that switch. Then, we compute the packet's finish number F_i^α and the packet's bid number B_i^α as follows:

if(α *is active*)
    $F_i^\alpha = F^\alpha + P_i^\alpha$;
else
    $F_i^\alpha = R(t_i^\alpha) + P_i^\alpha$;
endif

$B_i^\alpha = P_i^\alpha + MAX(F^\alpha, R(t_i^\alpha) - \delta^\alpha)$;
$F^\alpha = F_i^\alpha$;

If the packet arrives when there is no more free buffer space, packets are dropped in order of decreasing bid number until there is space for the incoming packet. The next packet sent on the output line is the one with the smallest bid number.

3.3. Components of a Fair Queueing server

It is useful to trace a FQ server's actions on packet arrival and departure. When a packet arrives at the server, it first determines the packet's conversation ID α. The server then updates the current round number $R(t)$. The conversation ID is used to index into the server state to retrieve the conversation's finish number F^α and offset δ^α. These are used to compute the packet's finish and bid numbers, F_i^α and B_i^α.

If the output line is idle, the packet is sent out immediately, else it is buffered. If the buffers are full, some buffered packets may need to be discarded. On an interrupt from the output line indicating that the next packet can be sent, the packet in the buffer with the smallest bid number is retrieved and transmitted.

From this description, we identify three major components of a FQ implementation: bid number computation, round number computation, and packet buffering. We discuss each component in turn.

Bid number computation

A FQ server maintains, as its internal state, the finish number F^α and the offset δ^α of each conversation α passing through it. An implementor has to make two design choices: determining the ID of a conversation, and deciding how to access the state for that conversation.

The choice of the conversation ID depends on the entity to whom fair service is granted (see the discussion in Chapter 2), and the naming space of the network. For example, if the unit is a transport connection in the IP Internet, one such unique identifier is the tuple (source address, destination address, source port number, destination port number, protocol type). The elements of the tuple can be concatenated to produce a unique conversation ID. For virtual circuit based networks, the Virtual Circuit ID itself can be used as the conversation ID.

Note that for the IP Internet, one cannot always use the source and destination port numbers, since some protocols do not define them. For example, if an IP packet is generated by a transport protocol such as NetBlt [17], this information may not be available. An engineering decision could be to recognize port numbers for some common protocols and use the IP (source address, destination address) pair for all other protocols. This may result in some unfairness since transport connections sharing the same address pair would be treated first-come-first-served.

The conversation ID is used to access a data structure for storing state. Since IDs could span large address spaces, the standard solution is to hash the ID onto a index, and the technology for this is well known [65]. Recently, a simple and efficient hashing scheme that ignores hash collisions has been proposed [93]. In this approach, some conversations could share the same state, leading to unfair service, since these conversations are served first-come-first-served. However, this can be attenuated by occasionally perturbing the hash function, so that the set of conversations that share the same state changes periodically.

Round number computation

The round number at a time t is defined to be the number of rounds that a bit-by-bit round robin server would have completed at that time. To compute the round number, the FQ server keeps track of the number of active conversations $N_{ac}(t)$, since the round number grows at a rate that is inversely proportional to N_{ac}. However, this computation is complicated by the fact that determining whether or not a conversation is active is itself a function of the round number.

Consider the following example. Suppose that a packet P_0^A of size 100 bits arrives at time 0 on conversation A, and let $L = 1$. During the interval [0,50), since $N_{ac} = 1$, and $\partial R(t)/\partial t = 1/N_{ac}$, $R(50) = 50$. Suppose that a packet of size 100 bits arrives at conversation B at time 50. It will be assigned a finish number of 150 (= 50 + 100). At time 100, P_0^A has finished service. However, in the time interval [50, 100), $N_{ac} = 2$, and so $R(100) = 75$. Since $F^A = 100$, A is still active, and N_{ac} stays at 2. At $t = 200$, P_0^B completes service. What should $R(200)$ be? The number of conversations went down to 1 when $R(t) = 100$. This must have happened at $t = 150$, since $R(100) = 75$, and $\partial R(t)/\partial t = 1/2$. Thus, $R(200) = 100+50 = 150$.

Note that each conversation departure speeds up the $R(t)$, and this makes it more likely that some other conversation has become inactive. Thus, it is necessary to do an *iterative deletion* of conversations to compute $R(t)$, as shown in Figure 3.1.

The server maintains two state variables, t_{chk} and $R_{chk} = R(t_{chk})$. A lower bound on $R(t)$ is $R_{chk} + L/N_{ac}(t_{chk})*(t - t_{chk})$, since N_{ac} is strictly non-increasing in [t_{chk}, t]. If some F^α is less than this expression, then conversation α has become inactive some time before time t. We determine the time when this happened, checkpoint the state at that time by updating the t_{chk}, R_{chk} pair, and repeat this computation till no more conversations are found to be inactive at time t.

Round number computation involves a MIN operation over the finish numbers, which suggests a simple scheme for efficient implementation. The finish numbers are maintained in a heap, and as packets arrive the heap is adjusted (since F^α is monotonically increasing for a given α, this is necessary for each incoming packet). This takes time O(log $N_{ac}(t)$) per operation. However, it only takes constant time to find the minimum, and so each step of the iterative

```
/* F, Δ and N are temporary variables */
N = N_ac(t_chk);
do:
        F = MIN(F^α | α is active);
        Δ = t − t_chk;
        if (F ≤ R_chk + Δ * L/N) {
                declare the conversation with F^α = F inactive;
                t_chk = t_chk + (F − R_chk) * N/L;
                R_chk = F;
                N = N − 1;
        }
        else {
                R(t) = R_chk + Δ * L / N;
                R_chk = R(t);
                t_chk = t;
                N_ac(t) = N
                exit;
        }
od
```

Figure 3.1: Round number computation

deletion takes time O(log $N_{ac}(t)$) (for readjusting the heap after the deletion of the conversation with the smallest finish number).

In related work by Heybey *et al*, a heuristic for computing the round number has been proposed [57]. In this scheme, the round number is set to the finish number of the packet currently being transmitted, and all packets with the same finish number are served first-come-first-served. If this heuristic (or a small variant) is acceptable, the round number can be easily computed.

Packet buffering

FQ defines the packet selected for transmission to be the one with the smallest bid number. If all the buffers are full, the server drops the packet with the largest bid number (unlike the algorithm in Chapter 2, this buffer allocation policy accounts for differences in packet lengths). The abstract data structure required for packet buffering is a *bounded heap*. A bounded heap is named by its root, and contains a set of packets that are tagged by their bid number. It is associated with two operations, `insert(root, item, conversation_ID)` and `get_min(root)`, and a parameter, MAX, which is the maximum size of the heap.

`insert()` first places an item on the bounded heap. While the heap size exceeds MAX, it repeatedly discards the item with the largest tag value. We insert an item before removing the largest item since the inserted packet itself may be deleted, and it is easier to handle this case if the item is already in the heap. To allow this, we always keep enough free space in the buffer to accommodate a maximum sized packet. `get_min()` returns a pointer to the item with the smallest tag value and deletes it.

Determining a good implementation for a bounded heap is an interesting problem. There are two broad choices.

1 Since we are interested only in the minimum and maximum bid values, we can ignore the conversation ID, and place packets in a single homogeneous data structure.

2 We know that, within each conversation, the bid numbers are strictly monotonically increasing. This fact can be used to do some optimization.

It is not immediately apparent what the best course of action should be, particularly since per-conversation queueing is computationally more expensive. Thus, we did a performance analysis to help determine the best data structure and algorithms for packet buffering. The next sections describe some implementation alternatives, our evaluation methodology, and the results of the evaluation.

3.4. Buffering alternatives

We considered four buffering schemes: an ordered linked list (LINK), a binary tree (TREE), a double heap (HEAP), and a combination of per-conversation queueing and heaps (PERC). We expect that the reader is familiar with details of the list, tree and heap data structures. They are also described in standard texts such as References [58, 78].

Ordered list

Tag values usually increase with time, since bid numbers are strictly monotonic within each conversation (though not monotonic across conversations). This suggests that packets should be buffered in an ordered linked list, inserting incoming packets by linearly scanning from the largest tag value. Monotonicity implies that most insertions are near the end, and so this reduces the number of link traversals required.

Binary tree

We studied a binary tree, since this is simple to implement and has good average performance. Unfortunately, monotonic tag values can skew the tree heavily to one side, and the insertion time may become almost linear. This skew can be removed by using self-balancing trees such as AVL trees, 2-3 trees or Fibonacci trees. However, the performance of the self-balancing trees is comparable to that of a heap, since operations on balanced trees as well as heaps require a logarithmic number of steps. Since we do study heaps, we have not evaluated self-balancing trees explicitly. Our performance evaluation of heaps will also be representative of the results for self-balancing trees.

Double heap

A heap is a data structure that maintains a partial order. The tag value at any node is the largest (or smallest) of all the tags that lie in the subtree rooted at that node. Since we require both the minimum and the maximum elements in the heap, we maintain two heaps (implemented as arrays) and cross pointers between them. The code for implementing double heaps is presented in Appendix 1.

Per-conversation queue (PERC)

We know that, within a conversation, bid numbers are strictly monotonic. So, we queue packets per conversation, and keep two heaps keyed on the bid numbers of the head and tail of the queue for each conversation. `insert()` adds a packet to the end of the per channel queue and updates the max heap. `get_min()` finds the packet with smallest bid number from the min heap and dequeues it.

3.5. Performance evaluation

The performance of a data structure is measured by the cost of performing an elementary operation, such as an insertion or a deletion of an element, on it. Traditionally, performance has been measured by the asymptotic *worst* case cost of the operation as the size of the data structure grows without bound. For example, the insertion cost into an ordered list of length N is O(N), since in the worst case we may need to traverse N links to insert an item into the list.

How should we measure the performance of the four buffering data structures for the `insert()` and `get_min()` operations? Since constant work is needed to add or delete a single item at a known position to any data structure, the unit of work for linked lists and trees is a link traversal and for heaps is a swap of two elements. For linked lists and trees, the time for `get_min()` is a constant, and, for the other two data structures, it is comparable to the insertion time. Thus, an appropriate way to measure the performance of the data structures is to measure the number of links of the data structure that are traversed, or the expected number of swaps, during an `insert()` operation. Let *B* denote the number of buffers in a gateway, and let *N* denote the number of conversations present at any time (*B* is typically much larger than *N*). Table 3.1 presents well known results for the performance of the data structures described above for the `insert()` operation.

	Best	Worst	Average (Uniformly random workload)
LINK	O(1)	O(B)	O(B)
TREE	O(1)	O(B)	O(log(B))
HEAP	O(log(B))	O(log(B))	O(log(B))
PERC	O(log(N))	O(log(N))	O(log(N))

Table 3.1: Theoretical insertion costs

While the asymptotic worst case cost is an interesting metric, we feel that it is also desirable to know the average cost. However, average case behavior is influenced by the workload (the exact sequence of `insert` and `get_min` operations) that is presented to the data structure. Thus the best that we can do analytically is to assume that the workload is drawn from some standard distribution (uniform, gaussian, and so on), and compute the expected cost. We believe that this is not adequate. Instead, we use a general analysis methodology that we think is practical, and has considerable predictive power.

Methodology

We first parameterize the workload by some (small) number of parameters. Suitable values of the parameters are then fed to a realistic network simulator to create a trace of the workload for those parameter values. Then, we implement the data structure and associated algorithms, and measure the average performance over the trace length. This enables us to associate an average performance metric at that point in the workload parameter space. By judicious exploration of the parameter space, it is possible to map out the average performance as a function of the workload, and thus extrapolate performance to regions of the space that are not directly explored.

In our opinion, this methodology avoids a significant difficulty in average case analysis, that is, reliance on unwarranted assumptions about the workload distribution. Also, by mapping algorithm performance onto the workload space, it enables a network designer to choose an appropriate algorithm given the operating workload.

The drawback with this method is that it requires a realistic network simulator, and considerable amounts of computing time. Further, the parameterization of the workload and the exploration of the state space are more of an art than a science. However, we feel that these drawbacks are more than compensated for by the quality of the results that can be obtained.

Evaluation results

We chose the scenario of Figure 3.2 for detailed exploration. The gateway serves multiple sources (each of which generates one conversation) that share two common resources: the bandwidth of the output (trunk) line, and buffers in the gateway. Since there are no inter-trunk service dependencies, it suffices to model a single output trunk. Further, by changing the number of sources, and the number of buffers, it is possible to drive the system into congestion, something that we want to study. Finally, it is simple enough that it can be easily parameterized. Thus, our choice.

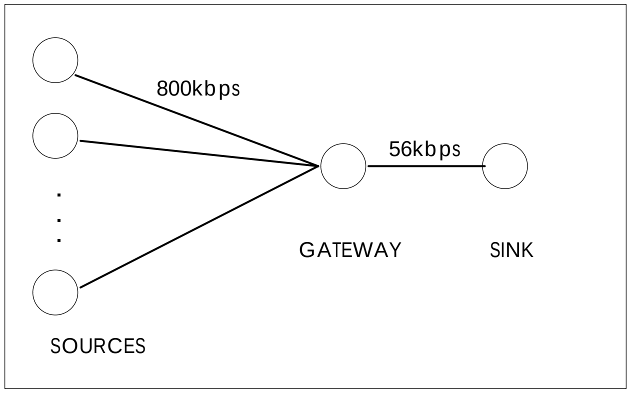
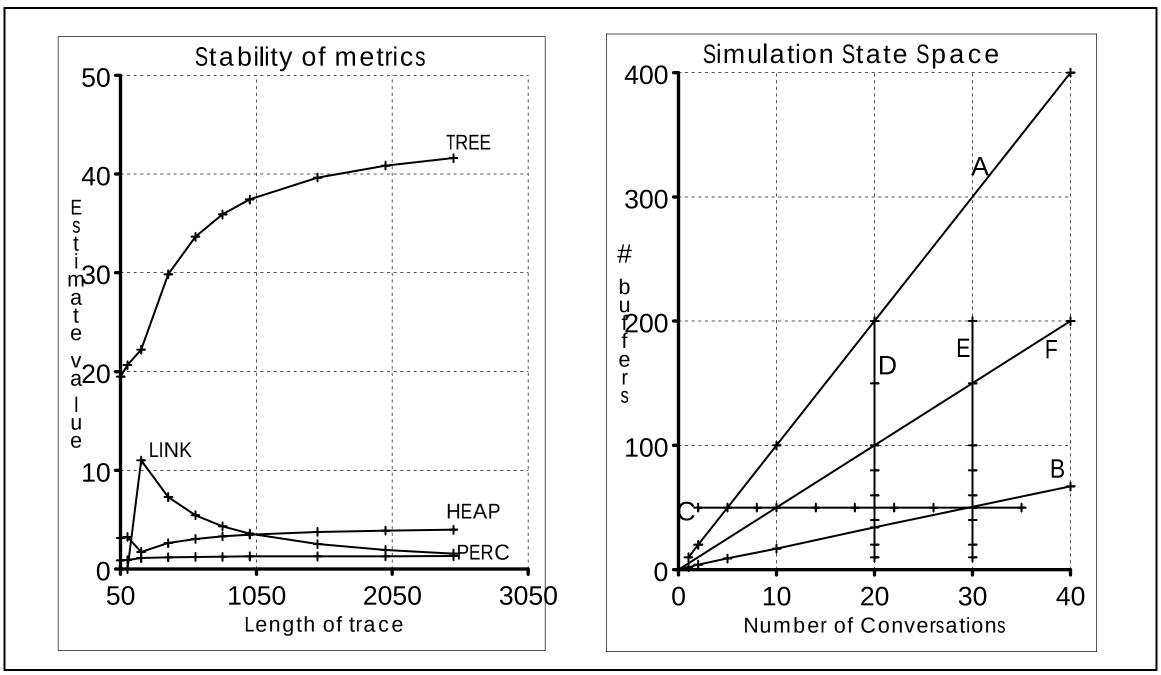


Figure 3.2: Simulation scenario



Figures 3.3 and 3.4

Note that we do not introduce any 'non-conformant' traffic in the sense of [57], since we wish to explore design decisions for well behaved sources only. If the network is expected to carry non-conformant traffic as well, then an evaluation of performance similar to the one described here needs to be carried out for that case.

The simulated sources obey the DARPA TCP protocol [108] with the modifications made by Jacobson [63]. They have a maximum window size of W each. By virtue of the flow control scheme, each source dynamically increases its window size, till either a packet is dropped by the gateway (leading to a timeout and a retransmission) or the window size reaches W. It is clear that the gateway cannot be congested if

$$W * N \leq B.$$

If the network is not congested, then each source behaves nearly independently, and the workload is regular, in the sense that the short term packet arrival and service rates are equal, and queues do not build up. When there is congestion, retransmissions and packet losses dramatically change the workload. Thus, one parameter that affects the workload is the ratio N/B. We also expect the workload to change as the number of conversations *N* increases. Thus, keeping *W* fixed, the two parameters that determine the workload are *N* and *B*.

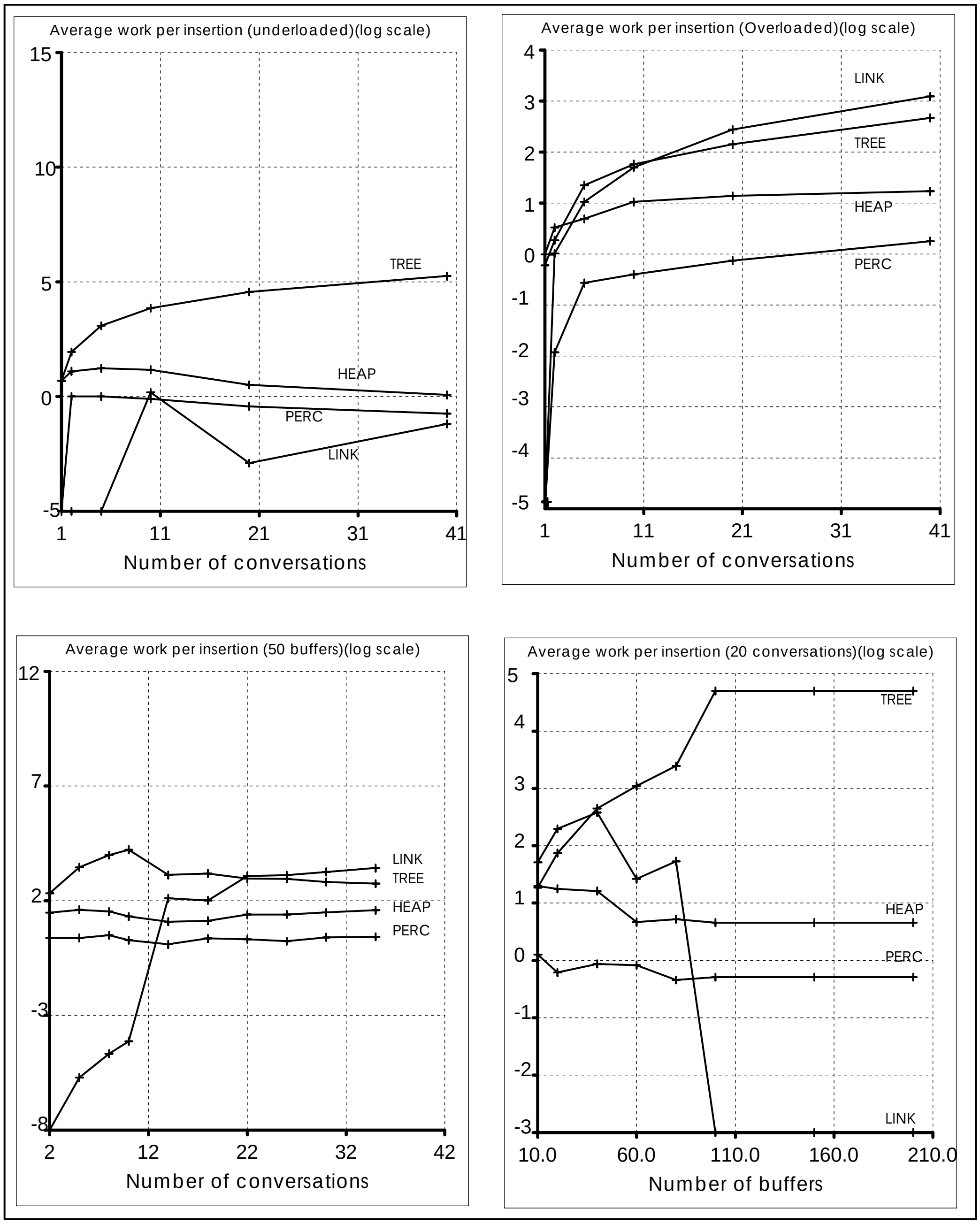


Figure 3.5: Average cost results

Following the experimental methodology outlined above, we used the REAL network simulator [73] to generate workload traces for a number of (*N*, *B*) tuples. One practical problem was to determine the appropriate trace length. Since generating a trace takes a considerable amount of computation, we decided to generate the shortest trace for which the cost metrics for all the four implementations stabilized. For simplicity, we determined this length for a single workload, with *N* = 10, *B* = 200, and generated a trace for 2500 seconds of simulated time. We then plotted the four cost metrics as a function of the trace length (Figure 3.3). We find that at 2500 seconds, all the metrics are no more than 10% away from their asymptotes. Since we only

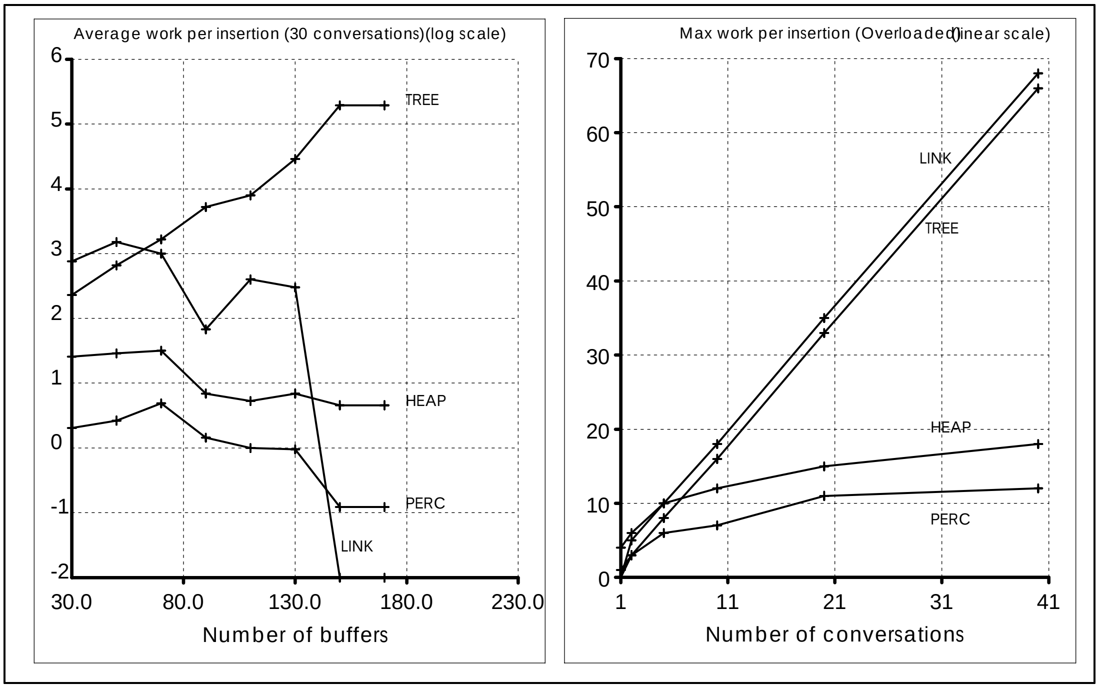


Figure 3.6: Average and maximum cost results

wanted to make qualitative cost comparisons, we generated each trace for 2500 seconds.

The (N, B) state space was explored along the five axes (labeled A through E) shown in Figure 3.4. Each '+' marks a simulation; there were a total of 35 simulations. Cost metrics for each implementation were determined along each axis. Axis A is the underloaded axis - along every point in the axis the gateway is lightly loaded, that is $W * N < B$. Symmetrically, axis B is the overloaded axis. Axes C, D and E are partly in the underloaded regime, and partly in the overloaded regime. Thus, congestion-dependent transitions in the relative costs of the implementations occur along these axes. The axis marked F is the locus of $W*N = B$.

Figures 3.5 and 3.6 show the average insertion cost along each of the five axes for each implementation. This is computed as

 # elementary operations / # insertions in the trace

where an elementary operation is the traversal of a single link or a single heap exchange. All Y axes, though marked linearly, are drawn to logarithmic scale, so that, for example, 2 corresponds to e^2. Conceptually, one can imagine that for each implementation, there is a performance surface overlaying the workload space. Figures 3.5 and 3.6 represent cross sections of these surfaces as we slice along axes A-E. We can extrapolate the surfaces from these cross sections.

Results

Examination of the surfaces points out several facts:

- The performance surfaces for all the implementations (except LINK) are generally smooth, with few discontinuities. Thus, extrapolating the curves is meaningful.
- LINK behavior is somewhat erratic, since the insertion cost is is highly dependent on the workload. However, it still has a well defined behavior: in some cases, it is the by far the cheapest implementation, in others, it is clearly the most expensive. Figure 3.7 divides the

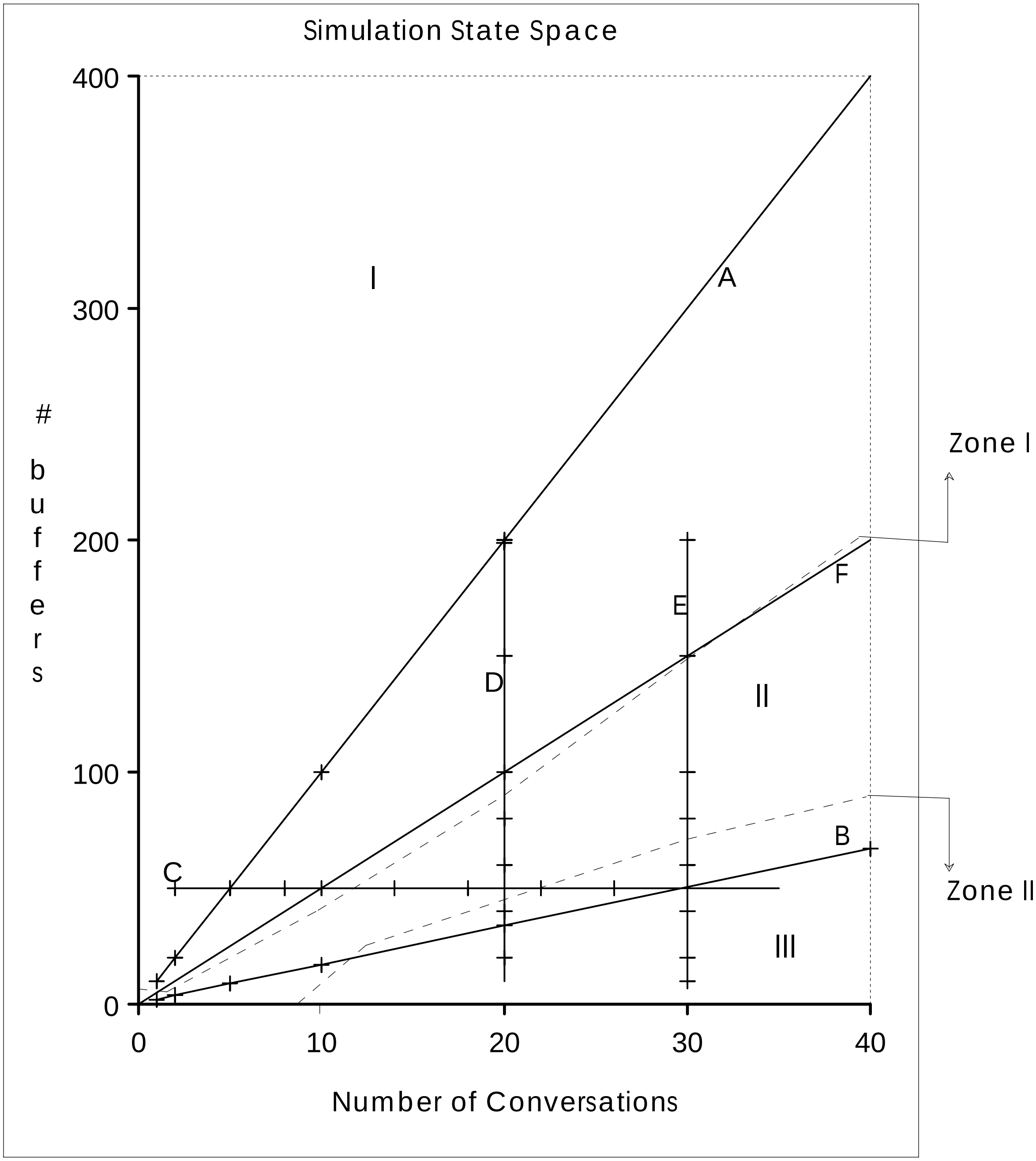


Figure 3.7: Linked list performance

workload space into three zones, numbered I-III. In zone I, it is best to use LINK, in zone III, LINK has the worst metric.

- As the number of conversations increases, the average HEAP and PERC insertion cost increases in the overloaded regime and is roughly constant in the underloaded regime.
- The cost metric for PERC is always less than that for HEAP or TREE.
- The cost metric for HEAP is within an order of magnitude of that for PERC in most cases.
- In the underloaded regime, binary trees become skewed, and hence are costly. They perform better in the overloaded regime.

- The average insertion cost for PERC is less than its theoretical average case cost.
- The maximum work done, which is shown for a typical case in Figure 3.6, is as expected in Table 3.1.
- In the underloaded case, HEAP and PERC show a declining trend, but this is offset by a larger increasing trend in the deletion time (not shown here).

Interpretation of results

The results give several guidelines for FQ implementation. TREE performs the worst in the underloaded regime; in the overloaded regime, HEAP and PERC are better. Hence, TREE is a bad implementation choice. We will not discuss it further.

Among the other strategies, PERC is always better than HEAP, and both of them have small worst case insertion costs. The worst case work per insertion is bounded by O(log(B)) for HEAP, and by O(log(N)) for PERC. Assuming that a gateway has 32 Mbytes of buffering per trunk line, and that packets are, on the average, 1Kbyte long, there will be at most on the order of 32K packets in the buffer. The number of conversations will be on the order of the square root of this number, i.e., around 200. With these figures, HEAP requires log(32K) ≈ 15, and PERC requires log(200) ≈ 8 elementary operations. Our simulations (Figure 3.5) show that in the trace driven simulation, the average work for HEAP and PERC is less than half of the worst case work. Thus, the average cost per insertion for PERC will be more like 4 elementary operations. This is a small price to pay to implement Fair Queueing.

The behavior of LINK (Figure 3.7) points to another implementation tactic. Note that in region I, LINK has the least cost. If the network designer can guarantee that the system will never enter the overloaded region (for example, by preallocating enough buffers for conversations, as in the Datakit network), then implementing LINK is the best strategy.

One consideration that is orthogonal to the insertion cost is implementation cost. For example, it is clear that implementing PERC involves much more work than implementing LINK. There are two implementation costs, corresponding to the work that is done independent of the number of elementary operations (static cost), and the work done per elementary operation (dynamic cost), respectively.

One simple metric to measure static cost is to measure the code size for `insert()`. We extracted the code for `insert()` and all the functions that it calls, for each implementation and placed it in a file. This file was compiled to produce optimized assembly code (in Unix, by the command cc -S -O -c). We then stripped the file of all assembler directives, leaving pure assembly code. Since this was done on a RISC machine, all instructions have the same cost, and the file length is a good metric of the complexity of implementing a given strategy. Table 3.2 presents this metric for the four implementations, normalized to the cost of implementing LINK.

Implementation	Static Cost	Dynamic Cost
LINK	1.0	5
TREE	1.1	18
HEAP	2.5	88
PERC	5.5	96

Table 3.2: Implementation cost

The dynamic cost was determined by examining the optimized assembly code, and counting the number of instructions executed per elementary operation. Table 3.2 presents the results. We did not specifically concentrate on reducing the number of instructions while writing the source code. We believe that the dynamic cost of the more expensive schemes can be considerably reduced by hand coding in assembly language.

To summarize, we draw four conclusions:

1. Implementing TREE is a bad idea.
2. HEAP provides good performance with low implementation cost.
3. PERC consistently provides the best performance, but has the highest implementation cost.
4. If the network designer can guarantee that the network never goes into overload, LINK is cheap to implement and has the minimum running cost.

3.6. Conclusions

In this chapter, we have considered the components of a FQ server, and have presented and compared several implementation strategies. Our work indicates that cheap and efficient implementations of FQ are possible. Along with the work done by McKenney [93] and Heybey et al [57], this work provides the practitioner with well defined guidelines for FQ implementation. We hope that these studies will encourage more implementations of Fair Queueing in real networks.

The performance evaluation methodology described here enables realistic evaluation of the average case performance of network algorithms. As LINK shows, this can lead to interesting results. We believe that a similar methodology can be used to evaluate a number of other workload sensitive network algorithms.

Finally, we believe that these results can be extended to other scheduling disciplines that are similar to Fair Queueing, such as the Virtual Clock algorithm [154]. Thus, our work has some generality of application.

3.7. Future work

This chapter does not examine hardware implementations of Fair Queueing. Given the need for faster packet processing in high speed networks, this is an obvious direction to pursue.

While we presented the means for the cost metric, we ignored the variance. This is because our simulations are completely deterministic. It would be useful to enhance the performance methodology described earlier to determine the variance and confidence intervals.

3.8. Appendix 3.A

A double heap consists of a pair of heaps. Since operations on one heap must be reflected in the other, we need pointers between the two instances of an element in the double heap. Since we represent heaps as arrays, pointers are indices, and we implement cross pointers using two integer arrays of indices.

The physical data structures used are four arrays, min, max, i_min, and i_max. min and max are the arrays that store the two heaps, one has the minimum element at the root, the other has the maximum. i_min[k] is the position in max of the kth element of min. i_max is defined symmetrically.

Every move in either heap must update i_min and i_max. We note that the only time an element is moved is when it is exchanged with some other element. We encapsulate this into an operation exchg() that swaps elements in the min or max heap, and simultaneously updates i_min and i_max so that the pointers are consistent. We actually need two symmetric operations, min_exchg() and max_exchg(), that swap elements in the min and max heap respectively. min_exchg() looks like the following:

```
min_exchg(a, b)      /* calls to swap are call by name */
{
swap(min[a], min[b]);
swap(i_max[i_min[a]], i_max[i_min[b]]);
swap(i_min[a], i_min[b]);
}
```

We now prove that this operation preserves pointer consistency, i.e. that i_min[i_max[a]] = a and i_max[i_min[a]] = a. Elements are inserted only in the last (say, nth) position in the heap, so the initial pointer positions are: i_min[n] = i_max[n] = n . It is easy to see that at the end of each min_exchg() operation, the pointers will remain consistent. Hence, by induction, pointers are always consistent.

Given the exchange operation, the rest of the heap operations are simple to implement. Heap insertion is done by placing data in the last element, and sifting up.

```
min_insert(data,num)
/* num is the current size of the heap */
{
ptr = num + 1;
min[ptr] = data;

for (; (ptr/2 >= 1) &&(min[ptr] < min (ptr/2]); ptr /=2)
    min_exchg(ptr, ptr/2);
}
```

Deletion is done by changing both the min and the max heaps, then adjusting them to recover the heap property.

```
min_delete()
{
int save;

min[1] = INFINITY;
save = i_min[1];
min_exchg(1,num);
```

```
min_adjust(1);

max[save] = -1;
max_exchg(save,num);
max_adjust(save);
}
```

Adjusting a heap consists of recursively sifting the marked element up or down as the case may be. Termination in a logarithmic number of steps is assured: because of the heap property, calls either go up the heap or down, and there can be no cycles.

```
min_adjust(a)
{
int smaller, smaller_son;

smaller = a;
if (min[a] < min[a/2]) smaller = a/2;
smaller_son = (min[lson(a)] < min[rson(a)]) ? lson(a) : rson(a);
if (min[smaller_son] < min[a]) smaller = smaller_son;
if (smaller != a)
    {
     min_exchg(a, smaller);
     min_adjust(smaller);        /* recursive call */
    }
}
```