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UNIVERSITY OF PADUA
DEPARTMENT OF INFORMATION ENGINEERING
MASTER DEGREE IN COMPUTER ENGINEERING

A.A. 2009/2010

BATCH SIZE ESTIMATE

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Last Update: Monday 15th March, 2010 20:34

Contents

| | | |
|----------|--|-----------|
| 1 | Introduction | 5 |
| 1.1 | Model, Scenario, Terminology | 6 |
| 2 | Batch Resolution | 8 |
| 2.1 | Binary Tree Algorithms | 9 |
| 2.1.1 | Basic Binary Tree | 9 |
| | Example | 11 |
| | Nodes addresses | 12 |
| | Tree traversal rules | 13 |
| | Real value approach | 13 |
| 2.1.2 | Modified Binary Tree | 14 |
| 3 | Batch Size Estimate Techniques | 17 |
| 3.1 | CBT | 17 |
| 3.2 | Cidon | 18 |
| 3.2.1 | Estimate accuracy | 20 |
| 3.3 | Greenberg | 22 |
| 3.3.1 | base b variant | 25 |
| 3.4 | Window Based | 26 |
| 4 | Initial batch size estimate | 27 |
| 4.1 | Cidon Evaluation | 27 |
| 4.2 | Greenberg Evaluation | 30 |
| 4.2.1 | base b Greenberg | 33 |
| 4.2.2 | Considerations | 33 |
| 4.3 | Modified Greenberg with MLE | 34 |
| 5 | Comparison | 35 |

| | | |
|----------|--|-----------|
| A | Appendix | 36 |
| A.1 | Probability | 36 |
| A.1.1 | Chebyshev's inequality | 36 |
| A.1.2 | Binomial Distribution | 36 |
| | Poisson Approximation | 36 |
| | Normal Approximation | 36 |
| A.1.3 | Poisson Distribution | 37 |
| A.1.4 | Normal Distribution | 37 |
| A.2 | Greenberg bounded m -moments | 37 |
| A.3 | CBT Estimate Experimental Distribution | 39 |
| A.4 | Greenberg Estimate Distribution | 45 |

List of Figures

| | | |
|-----|--|----|
| 2.1 | <i>BT</i> : Batch split probabilities | 11 |
| 2.2 | <i>BT</i> : Basic binary tree example | 12 |
| 2.3 | <i>MBT</i> : Modified binary tree example | 15 |
| 3.1 | <i>CBT</i> : example | 18 |
| 3.2 | <i>Cidon</i> : initial split | 20 |
| 3.3 | <i>Basic Greenberg</i> : batch split idea | 23 |
| 4.1 | <i>Cidon</i> : Variance behavior | 28 |
| 4.2 | <i>Cidon</i> : Minimum p_ϵ required for accuracy k | 29 |
| 4.3 | <i>Cidon</i> : Upper bounds on the expected time (in slots) required to achieve accuracy k | 30 |
| 4.4 | <i>Basic Greenberg</i> : small 2^k sizes distribution. | 31 |
| 4.5 | <i>Basic Greenberg</i> : large 2^k sizes distribution. | 32 |
| 4.6 | <i>Basic Greenberg</i> : general sizes distribution. | 32 |

List of Tables

| | | |
|-----|--|----|
| 3.1 | <i>Basic Greenberg</i> Expected Estimate | 24 |
| 3.2 | <i>Greenberg</i> : different b summary | 26 |
| A.1 | Experimentally computed CBT Estimate Distributon | 40 |
| A.2 | Analytically computed basic Greeenberg Estimate Distribution | 46 |

Chapter 1

Introduction

Generally speaking a set of actors contending for a common resource define a *conflicting set*. As always, limited resources require policies to access them in an efficient and hopefully fair way. When the system is distributed, and this is our business, resource access can be assimilated to a coordination problem.

Physical medium access is our contended resource and several stations to the same physical medium to share it.

At the beginning of computer networks, multiple access channel (MAC) was a big issue for efficient communications: as consequence packet switched buffered networks were introduced reducing the conflicting set to only two stations and simplifying the original problem. Other the other hand switched networks could be realized only because the medium was wired: in fact a large collision domain could be sliced into smaller pieces and joined again together in ring, star or mesh structures.

In a wireless context the problem can be no more avoided.

Nowadays wireless connectivity in pervasive computing has ephemeral character and can be used for creating ad-hoc networks, sensor networks, connection with RFID (Radio Frequency Identification) tags etc. The communication tasks in such wireless networks often involve an inquiry over a shared channel, which can be invoked for: discovery of neighboring devices in ad-hoc networks, counting the number of RFID tags that have a certain property, estimating the mean value contained in a group of sensors etc. Such an inquiry solicits replies from possibly large number of terminals.

In particular we analyze the scenario where a reader broadcasts a query to the in-range nodes. Once the request is received, devices with datas of interest are all concerned in

transmitting the information back to the inquirer as soon as possible and, due to the shared nature of the communication medium, while collision problems come in: only one successful transmission at time can be accomplished, concurrent transmissions result in noise and an inefficient waste of energy/time since the channel is going to be occupied for some more time in future. This data traffic shows a bursty nature which is the worst case for all shared medium scenarios.

This problem is referred in literature with different names: *Batch Resolution Problem*, *The Reader Collision Problem*, *Object Identification Problem*. Algorithms trying to solve this problem efficiently are defined as *Batch Resolution Algorithms* (BRA) or *Collision Resolution Algorithms* (CRA).

For our terminology, given a query, it determines a subset of nodes which have to reply to it with one (and only one) message: this set of nodes constitutes our *batch*. The size of the batch can be known in advance, in lucky and optimistic scenarios, or it can change in function of the query or time.

Since each node has exactly one message to deliver, the problem of obtaining all the messages or counting the number of nodes involved by the resolution process is exactly the same.

Instead the problem differs when we are not so interested in the exact number of nodes but we would appreciate an estimate of the actual batch size, rather accurate if it is possible.

The knowledge of the batch size n is an important factor for parameter optimization, for efficient resolution trying to minimize the time taken by the process.

1.1 Model, Scenario, Terminology

We consider the following standard model of a multiple access channel. A large number of geographically dispersed nodes communicate through a common channel. Any node generates and transmits data on the channel. Transmissions start at integer multiples of time unit and last one unit of time, also called a “slot”.

For this condition to be true in SLOTTED ALOHA, there must be some forms of synchronization that inform the nodes about the beginning of the new slot (or at least the beginning of a cycle of slots). Slot size is equal to the fixed packet transmission time

and a node can start a transmission only at the beginning of the slot, otherwise it will stay quiet until the next slot will come.

In CSMA networks each node is able to determine the beginning of a new slot by sensing to the channel: when the channel is listened free a device can start transmitting its message. In our scenario we assume that all the transmitted messages have a fixed length. Once a node has started transmitting it can sense no more to the channel and consequently it cannot be aware of the result of its transmission until it receives feedback. For this reason we have that a transmission always takes the same time, either if it results in a success or a collision. On the other hand empty slots takes less time than transmissions.

CSMA/CD is not suitable for pervasive wireless devices such as sensors or RFID tags since they have to be keep as simple as possible to satisfy energy and cost requirements: they do not implement this MAC scheme and so no detection/reduction of collision time is possible.

We assume that there is no external source of interference and that a transmission can fail only when a collision takes place. In each slot, when k nodes transmit simultaneously, the success or the transmission depends on k :

- if $k = 0$ then no transmission are attempted. The slot is said to be *empty* or *idle*;
- if $k = 1$ then the transmission succeeds. The slot is said to be *successful*;
- if $k \geq 2$ there is a conflict, meaning that the transmission interferes destructively so that none succeeds. The slot is said to be *collided*.

We assume that nodes having new messages to deliver generated after the start of the resolution process will wait until the end before proceeding with their delivery.

Chapter 2

Batch Resolution

The general idea is as follows: the reader probes a set of nodes, and the nodes reply back. Since devices we consider operate in the wireless medium, collisions will result whenever a reader probes a set of nodes. The batch resolution algorithms use anti-collision schemes to resolve collisions. There are many algorithms that enable batch resolution, and these can be classified into two categories: (a) *probabilistic*, and (b) *deterministic*.

In *probabilistic algorithms*, a framed ALOHA scheme is used where the reader communicates the frame length, and the nodes pick a particular slot in the frame to transmit. The reader repeats this process until all nodes have transmitted at least once successfully in a slot without collisions.

Deterministic algorithms typically use a slotted ALOHA model, where the reader identifies the set of nodes that need to transmit in a given slot, and tries to reduce the contending batch in the next slot based on the result in the previous slot. These algorithms fall into the class of tree-based algorithms with the nodes classified on a binary tree based on their id, and the reader moving down the tree at each step to identify all nodes.

Deterministic algorithms are typically faster than probabilistic schemes in terms of actual node response slots used, however, they suffer from reader overhead since the reader has to specify address ranges to isolate contending tag subsets using a probe at the beginning of each slot.

Deterministic schemes assume that each node can understand and respond to complex commands from the reader, such as responding only if the *id* is within an address range specified by the reader. So not every device is able to support this class of algorithms. For

example passive tags, which are the **most dummy** devices, cannot understand this kind of requests and will continue to transmit in every resolution cycle, which lengthens the total time needed. Wireless sensors, semi-active and active tags should allow to implement tree-based algorithms: the reader can acknowledge nodes (immediate feedback) that have succeeded at the end of each frame, and hence those nodes can stay silent in subsequent slots, reducing the probability of collisions thereby shortening the overall identification time. Usually a node that successfully transmit its message and **it?** stays in silent until the end of the algorithm is said *resolved*.

They also assume a slotted model, and not a framed model, wherein the reader responds before and/or after every slot, adding overhead to the resolution.

Furthermore, since tree algorithms require explicit feedback about channel status, they force devices to be always active and listening to the channel in each step of the algorithm. On the other hand windows based algorithms are more energy saving since a device can sleep for most of time in the transmission window and only to wake up in the slot it has decided to transmit. In a windows of w slots a node will be up only for $1/w$ of time and wait for feedback at the end of the window.

Most of the batch resolution algorithm were originally developed for ALOHA based scenarios.

These algorithms can be flawlessly ported to the CSMA scheme:

- by utilizing empty slots as “ALOHA slot delimiters”
- by explicitly sending a slot delimiter marker.

2.1 Binary Tree Algorithms

Basic binary tree algorithm was first introduced by Capetanakis [5] in 1979.

2.1.1 Basic Binary Tree

At slot τ we have a batch \mathcal{B} of size n .

When a batch resolution process starts, initially all the nodes try to transmit and we can have 3 different events: *idle*, *success*, *collision*.

The supervisor broadcast the result of the transmission to all the nodes.

If we get *idle* or *success* events the resolution process stop meaning respectively that there were no nodes to resolve or there was only one node and that node's message was successfully received. That node delivered its message and will no longer take part in the

current batch resolution.

If we got a *collision* we know that at least 2 nodes are present and we have to solve the collision to obtain their messages. In this case all the n nodes play the algorithm.

Each node choose to transmit with probability p and to not transmit with probability $1 - p$. Nodes that choosed to transmit are said to own to set \mathcal{R} while the others to set \mathcal{S} . Of course $\mathcal{R} \cap \mathcal{S} = \emptyset$ and $\mathcal{B} = \mathcal{R} \cup \mathcal{S}$

Nodes in \mathcal{S} wait until all terminal in \mathcal{R} transmit successfully their packets, then they transmit.

Nodes in \mathcal{R} are allowed to transmit in slot $\tau + 1$.

Intuitively we can think that choosing with equal probability ($p = 1/2$) between retransmitting or waiting can be a good choice. This is the case, since the algorithm is in some sense “symmetric”, but this is not true in general, as we will see for MBT. Since $p = 1/2$ we can think to simply toss a coin to split the batch.

Algorithm 1 COLLISION BINARY TREE (\mathcal{B})

// current slot status can be *idle*, *success*, *collision*

Input: \mathcal{B} batch with $|\mathcal{B}| = n$

each node transmit its message

if (*idle* or *success*) **then**

 conflict resolution ended.

else

 each node flip a coin

$\mathcal{R} \leftarrow \{ \text{nodes that flipped head} \}$

$\mathcal{S} \leftarrow \{ \text{nodes that flipped tail} \}$

 COLLISION BINARY TREE (\mathcal{R})

 COLLISION BINARY TREE (\mathcal{S})

end if

Let L_n be the expected running time in slots required to resolve a conflict among n nodes using SBT. Let $Q_i(n) = \binom{n}{i} p^i (1 - p)^{n-i}$ the probability that i among n nodes decide to transmit in the next slot (probability that $|\mathcal{R}| = i$). So if i nodes decide to transmit we have first to solve a conflict of size $|\mathcal{R}| = i$ with expected time L_i and later a conflict of size $|\mathcal{S}| = n - i$ with expected time L_{n-i} . L_n is given by the cost of the current slot (1) **plus the expected time to solve all the possible decompositions of the current set**. L_n can be recursively computed (considering the factorial in $Q_i(n)$) collecting L_n in the

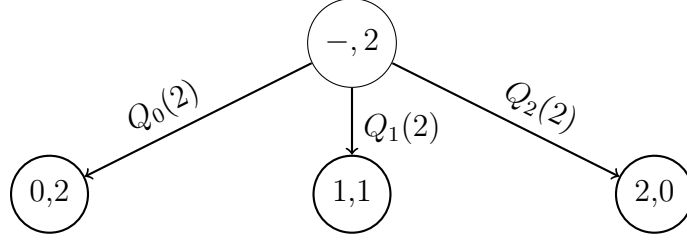


Figure 2.1: Transaction probabilities to split a set of 2 elements into two sets with i, j elements

following:

$$L_n = 1 + \sum_{i=0}^n Q_i(n)(L_i + L_{n-i}) \quad (2.1)$$

with

$$L_0 = L_1 = 1$$

To obtain an upper bound on the expected time as $n \rightarrow \infty$ further analysis techniques has to be used but here we want simply focus on how the algorithm behaves when n grows.

| | | | | |
|-----------------|--------------------|--------------------|--------------------|--------------------|
| $L_2 = 5.0000$ | $L_7 = 19.2009$ | $L_{12} = 32.6238$ | $L_{17} = 48.0522$ | $L_{22} = 62.4783$ |
| $L_3 = 7.6667$ | $L_8 = 22.0854$ | $L_{13} = 36.5096$ | $L_{18} = 50.9375$ | $L_{23} = 65.3636$ |
| $L_4 = 10.5238$ | $L_9 = 24.9690$ | $L_{14} = 39.3955$ | $L_{19} = 53.8227$ | $L_{24} = 68.2489$ |
| $L_5 = 13.4190$ | $L_{10} = 27.8532$ | $L_{15} = 42.2812$ | $L_{20} = 56.7078$ | $L_{25} = 71.1344$ |
| $L_6 = 16.3131$ | $L_{11} = 30.7382$ | $L_{16} = 45.1668$ | $L_{21} = 59.5930$ | $L_{26} = 74.0198$ |

Considering the efficiency $\eta_n = n/L_n$ (messages over slots) we have a decreasing serie $\eta_1 = 1, \eta_2 = 0.40, \eta_3 = 0.3913, \dots, \eta_{16} = 0.3542, \dots, \eta_{31} = 0.3505$. It can be shown [5] that $\eta_\infty \approx 0.347$.

Since the algorithm is much more efficient in solving small batches respect to large ones we would prefer to have (ideally) n batches of size 1 rather than 1 batch of size n . So knowing exactly the cardinality n of the initial batch \mathcal{B} can be used to split the nodes into small groups and resolve them faster.

This is the idea behind many improvements over the basic binary tree algorithm and it shows the importance of having an accurate estimate of n when the cardinality is initially unknown.

Example

In Figure 2.2 we provide an example to further investigate the behavior of the algorithm. We notice that the instance start with a collision in slot 1. Then nodes n_1, n_2, n_3 decide

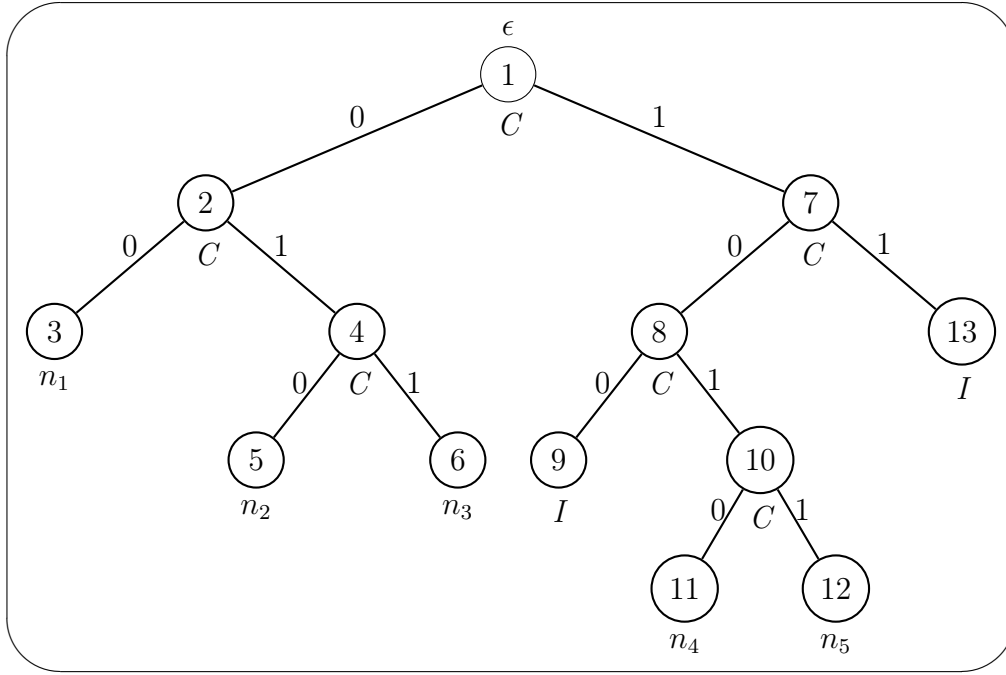


Figure 2.2: An instance of the binary tree algorithm for $n = 5$ nodes. The number inside the each circle identifies the slot number. The label below identifies the event occurring: I for *idle*, C for *collision*, n_i for resolution of node i . 0/1 branches is analogous to head/tail.

to proceed with a retransmission while n_4 , n_5 remain idle. In slot 2 we see another collision, after it n_1 decide to transmit again while n_2 and n_3 to stay quiet. In slot 3 we have the first resolution, n_1 send successfully its message and won't no more take part to the collision resolution.

We notice that we can know the cardinality of a collision only after it has been fully resolved. For example we know only after slot 6 that the collision in slot 2 involved 3 nodes.

Nodes addresses

Looking carefully to the tree you can see that each node resolved is characterized by an *address*: the path from the root to node n_i gives a string of bits. For example node n_4 's address has as prefix 1010. The prefix in this case can be equivalent to the address but, in a more general case, node address can be a longer string. Assuming in fact that node n_4 's full address is the 8 bit long string 10100010, running the algorithm brings to the discovery of only the first 4 bits since the collision become resolved without requiring further split of the batch and deeper collision tree investigation (collision in level t provokes a split and a deeper investigation in the tree at level $t + 1$ and it requires to

consider bit $t + 1$ of the nodes' addresses).

Tree traversal rules

The inquirer must provide feedback about the event in a slot but tree walking can be either explicit or implicit. It is explicit if, with feedback, the reader provide also the address in the root of the currently enabled sub-tree. Otherwise it is said to be implicit and each node compute autonomously the new enabled sub-tree.

We assume, following the conventional approach, to visit the tree in pre-order, giving precedence to sub-trees starting with 0.

Initially all nodes are enabled so the prefix is the empty string $\epsilon = b_{1..0}$, the root address. ϵ is considered to be prefix of any string.

Let $b_{1..k}$, with $b_i \in \{0, 1\}$, $k \geq 0$, be the current enabled k -bit prefix and $event \in \{I, S, C\}$.

The possible cases are: **qui incasino un po' le cose con una notazione un po' imprecisa**

- i. $event$ is C : no matter about $b_{1..k}$, next enabled interval will be $b_{1..k}0$;
- ii. $event$ is not C and $b_k = 0$: we successfully resolved the left part of the sub-tree, now we will look for right one. Next enabled prefix will be $b_{1..k-1}1$;
- iii. $event$ is not C and $b_k = 1$: we completed the resolution of a left sub-tree, now we will look in the way back to the root for the first right sub-tree still unresolved. Let t be $\arg \max_{i \in 1..k} b_i = 0$ (or $t \leftarrow 0$ if $b_{1..k}$ having 1 or more 1), in other words the position of the right most 0 in the prefix, if any. The new enabled interval will be $b_{t-1}1$. You can see this rule applied after slot 6 and 12 in the example;
- iv. termination condition is checking $b_{1..k} = \epsilon$.

Real value approach

Decidere se inserire o meno le considerazioni sulla visione degli indirizzi (alias ID) dei nodi come numeri reali tra 0 e 1 e della risoluzione come intervalli reali abilitati contenenti un solo nodo. Utile per collegarsi a popovski/cidon e alla suddivisione in insiemi in generale
Every length binary string can be also interpreted as a real number in the interval $[0, 1)$

$$11001 \leftrightarrow 1 \cdot 2^{-1} + 1 \cdot 2^{-2} + 0 \cdot 2^{-3} + 0 \cdot 2^{-4} + 1 \cdot 2^{-5}$$

by associating to each position in the string a different power of 2.

In general a given a string $\mathbf{b}_i = (b_{i1}b_{i2}b_{i3} \dots)$, with $b_{ij} \in \{0, 1\}$, can be associated to a

real number $r_i \in [0, 1)$ by a bijective map r :

$$r_i = r(\mathbf{b}_i) = \sum_{j=1}^{\infty} \frac{b_{ij}}{2^j} \quad (2.2)$$

So we could think, instead of tossing a coin only when needed, to initially flip a coin, in the same manner, L times to get a L -bits randomized string. In this way each node can be immediately be assigned to a set of length 2^{-L} . There are 2^L relatively ordered distinct sets in the interval $[0,1)$.

Given a finite control string $\mathbf{a}_i = (a_{i1}a_{i2} \dots a_{ik})$, it enables all the nodes identified by real number x within the interval:

$$r(\mathbf{a}_i) \leq x < r(\mathbf{a}_i) + 2^{-k} \quad (2.3)$$

QUESTA OSSERVAZIONE è SOLO FRUTTO DEL MIO SACCO E MI SEMBRAVA INTERESSANTE.

An interesting observation is that the distribution of the nodes into the real interval depends upon p , the probability to obtain 0 or 1 tossing a biased coin. è interessante perchè per il basic binary tree p ottimo è 0.5 per cui si ottiene una distribuzione sperabilmente uniforme dei nodi (o poisson?). Mentre 0.5 non è ottimo per il Modified binary tree: p ottimo 0.4175. quindi la distribuzione migliore per il MBT è una specie di esponenziale discreta e la profondità dell'albero aumenta più ci si avvicina a 1. Questo è quello che mi dice l'intuizione e non ho visto scritto da nessuna parte (magari sul paper originale del MBT c'è). per cui il MBT non può essere utilizzato banalmente per fare stime tramite una risoluzione parziale di un qualunque sotto intervallo $[0, x)$ con k nodi poichè $n \neq \frac{k}{x}$ (popovski) a meno che non sia nota la distribuzione dei nodi $f(x)$ e si normalizzi per $f(x)$ al posto che x . NOTA: in popovski pg 295 dicono *To summarize, we can say that without any modification, the BT (or the MBT) algorithm offers a way to estimate the unknown conflict multiplicity.* il che è ok ma solo se MBT usa $p=0.5$ per cui $f(x) = x$. studiare $f(x, p)$?

2.1.2 Modified Binary Tree

Modified binary tree is a simple way to improve the basic variant for the binary tree algorithm.

The observation is that, during the tree traversal, sometimes we know in advance if the next slot there will be collided. This happens when, after a collided slot (τ), we get and

idle slot ($\tau + 1$) in the left branch of the binary tree: visiting the right branch ($\tau + 2$) we will get a collision for sure.

In fact in slot (τ) we know that in the sub-tree there are at least 2 nodes and none of them owns to the left-branch sub-tree ($\tau + 1$). So they must be in the right sub-tree and when enabled to transmit ($\tau + 2$) transmissions will disrupt. Solution is to keep previous node ($\tau + 2$) as a virtual node, to skip it, and continue visiting node ($\tau + 1$).*sibling.leftchild* in slot ($\tau + 2$). This let us save a slot.

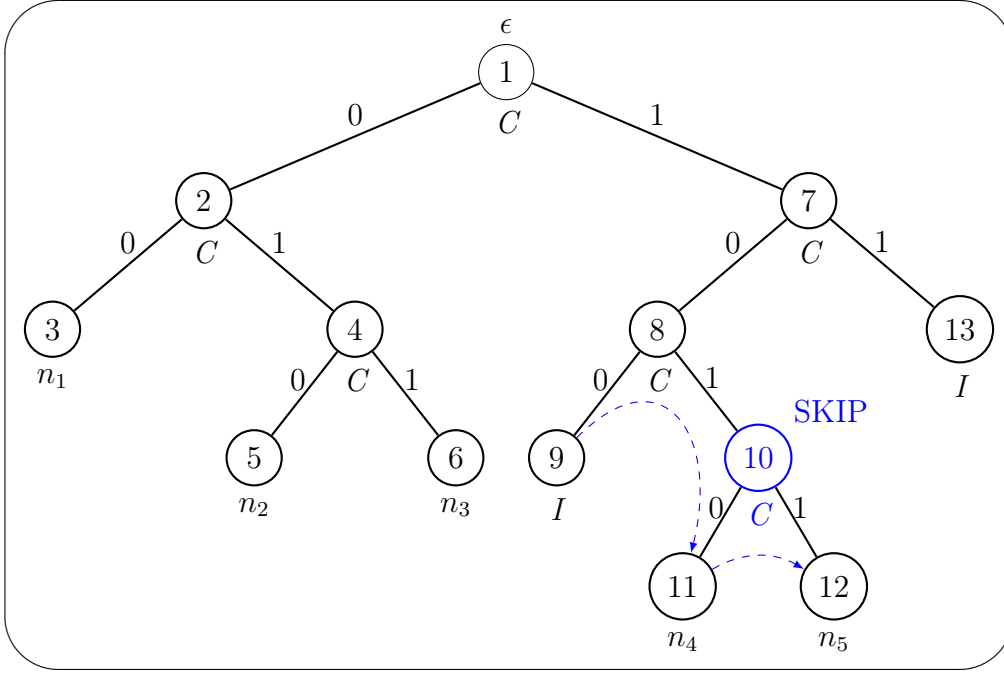


Figure 2.3: Same example as in Figure 2.2 but using MBT: tree structure do not change but node 10 is skipped in the traversal. $\tau = 8$

Expected time analysis is analogous to section 2.1.1. **The only difference is that after a collision, if we get an idle slot, we will skip the “next one” (and we won’t pay for it). So we can see that the expected slot cost is $[1 \cdot (1 - Q_0(n)) + 0 \cdot Q_0(n)]$.** Then

$$L_n^{MBT} = (1 - Q_0(n)) + \sum_{i=0}^n Q_i(n)(L_i^{MBT} + L_{n-i}^{MBT}) \quad (2.4)$$

with

$$L_0^{MBT} = L_1^{MBT} = 1$$

Intuitively in this case, since an higher probability to stay silent, reduces the expected slot cost, optimal transmit probability won’t no more be $1/2$. At the same time lowering the

transmit probability will increase the number of (wasted) idle slots. So the new optimal probability p will be somewhere in the interval $(0, 1/2)$.

It can be shown¹ that best achievable result is for $p = 0.4175$ and, with this p , efficiency $\eta \approx 0.381$ as $n \rightarrow \infty$ which is asymptotically +10% faster than basic BT.

In general we have:

$$L_n \leq C \cdot n + 1 \quad \text{where} \quad C = 2.622 \quad (2.5)$$

Not using optimal probability for p but $1/2$ results, for large n , in about 0.2% peak performance loss ($C = 2.667$) which is a really moderate decrease.

What is even more important is that 0.4175 is close to the optimal bias for small n as well.

¹ J.L. Massey, *Collision-Resolution Algorithms and Random-Access Communications*, CISM Courses and Lectures, vol. 265, pp. 73–137. Springer, Berlin (1981)

Chapter 3

Batch Size Estimate Techniques

We present here some noteworthy techniques for batch size estimate that can be found in literature. If the technique was not already identified by a name or associated to a acronym we used the name of one authors as reference.

In general, we assume not to have any *a priori* statistical knowledge about the multiplicity of the nodes involved in a collision. So estimation techniques must provide efficient ways to obtain an estimate for the general zero-knowledge scenario.

3.1 CBT

The most simple idea to obtain an estimate of the batch size could be to solve a minimum amount of nodes to obtain an estimate. This can be done, for example, by using deterministic algorithms such as CBT.

CBT is a partial resolution algorithm since only a fraction of the packets of the batch are successfully transmitted. The clipped binary tree algorithm is identical to the modified binary tree algorithm (with $p = 1/2$ since we require the nodes to be uniformly distributed in the interval $[0,1)$) except that it is stopped (the tree is clipped) whenever two consecutive successful transmissions follow a conflict.

When the algorithm stops we know than the last two nodes resolved owns to the same level i of the tree (root is at level=0).

We could think to obtain an estimate as:

$$\hat{n} \leftarrow 2^i \tag{3.1}$$

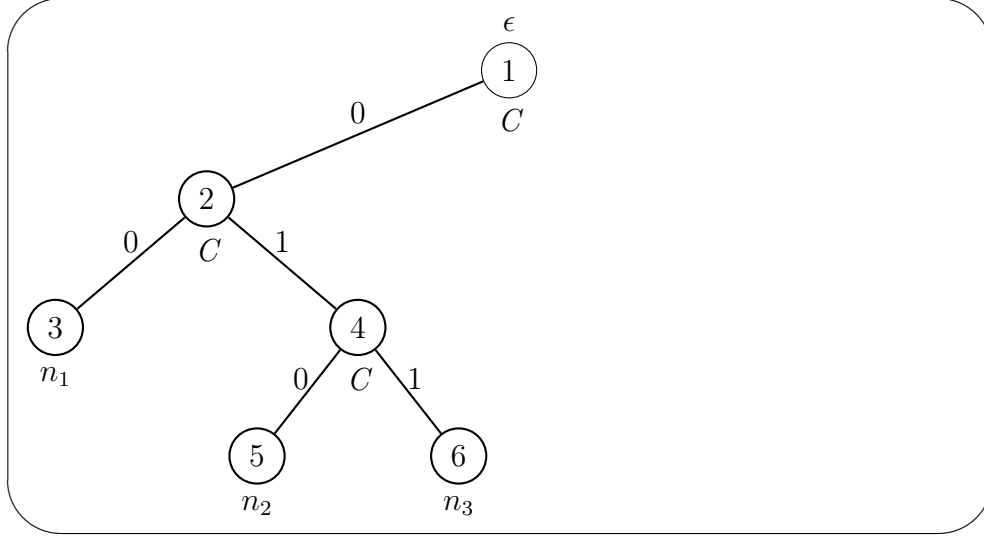


Figure 3.1: Same example as in Figure 2.2 but resolution using CBT ends up after two consecutive successful transmissions.

Experimental results show that the variance of the obtained estimate is extremely high and the resulting accuracy is really poor.

This is due to the fact that the batch of interest we use for the estimate becomes, at each level, smaller and smaller: the estimate, even for huge sizes, depends only on very few (3-5) nodes (those with lower addresses). So estimate is quite unstable.

Results are reported in Appendix in tables A.1. Notice how slowly the distribution probability decrease.

3.2 Cidon

Cidon and Sidi proposed this approach in [3]. In this work they describe a complete resolution algorithm based on two phases:

1. to get an estimate of the initial batch using a partial deterministic resolution scheme.
2. to perform an optimized complete deterministic resolution basing on the results of phase 1.

The strategy adopted to obtain the estimate is to resolve a small portion of the batch and to accumulate the number of successful transmission resulted.

Initially we fix a probability p_ϵ that determines how the whole batch is split at the very first time.

We named it p_ϵ to underline that this initial choice reflects on the expected accuracy of the resulting estimate.

As usual we have initially a batch \mathcal{B} of unknown size n . At the beginning of the algorithm each node chooses to transmit with probability p_ϵ . Thus the n nodes are partitioned into two sets \mathcal{E} and \mathcal{D} , where \mathcal{E} consists of those that transmitted and \mathcal{D} the rest. Clearly, $|\mathcal{E}| + |\mathcal{D}| = n$. If the resulting slot is empty or contains a successful transmission, we conclude that $|\mathcal{E}| = 0$ or $|\mathcal{E}| = 1$, respectively. If a conflict occurs, it is known that $|\mathcal{E}| \geq 2$, and the nodes in \mathcal{E} use a complete batch resolution algorithm to resolve the conflicts among the nodes in \mathcal{E} . At the end of this part we know the exact value of \mathcal{E} by accumulating the number of successful transmissions during the resolution. We call this counter j . So, after this estimation phase, since we expect that the nodes are uniformly distributed in the real interval $[0,1)$ and we solved the first part of the interval from 0 to p_ϵ we found that our expected density can be supposed to be $\frac{j}{p_\epsilon}$. Then we simply compute our estimate \hat{n} as:

$$\hat{n} \leftarrow \frac{j}{p_\epsilon} \quad (3.2)$$

In this case, since we already resolved the nodes in \mathcal{E} , we are more interested only in the cardinality of the remaining batch to solve \mathcal{D} which we can compute as:

$$\hat{k} = E[\text{size}(\mathcal{D})] \leftarrow \frac{j}{p_\epsilon}(1 - p_\epsilon) \quad (3.3)$$

Algorithm 2 CIDON

Input: p_ϵ , fraction of the whole batch to solve

- 1: // Phase 1
 - 2: each node flip a coin getting 0 with probability p_ϵ , 1 otherwise
 - 3: $\mathcal{E} \leftarrow \{\text{nodes that flipped 0}\}$
 - 4: $\mathcal{D} \leftarrow \{\text{nodes that flipped 1}\}$
 - 5: COMPLETE COLLISION RESOLUTION (\mathcal{E})
 - 6: $\hat{k} \leftarrow |\mathcal{E}|/p_\epsilon$
 - 7: // Phase 2
 - 8: OPTIMIZED COMPLETE COLLISION RESOLUTION ($\mathcal{D}, \hat{k}, p_\epsilon$)
-

Note that $|\mathcal{E}| = 0$ does not imply $|\mathcal{D}| = 0$ so a complete resolution algorithm has always to be performed on \mathcal{D} . Recalling subsection “Real Value Approach” in 2.1.1, operation on line 2 in Alg. 2 is equivalent to force each node to generate a unique ID expressed as a

fixed length real value in the interval $[0,1)$.

Following Figure 3.2 show the case providing a simple example.

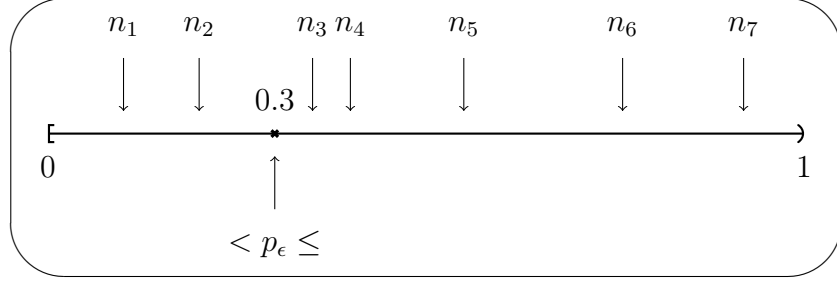


Figure 3.2: In this example $p_\epsilon = 0.3$. At the beginning of the algorithm each node generate its own ID. Nodes whose ID is less than p_ϵ owns to \mathcal{E} . Nodes whose ID is greater or equal to p_ϵ owns to \mathcal{D} . Estimate of the batch returns $\lceil 2/0.3 \rceil = 7$ which, in this case, is the exact size of the batch.

Procedure COMPLETE COLLISION RESOLUTION (\mathcal{E}) identifies any procedure able to resolve all the nodes in \mathcal{E} allowing them to successfully transmit their messages while OPTIMIZED COMPLETE COLLISION RESOLUTION ($\mathcal{D}, \hat{k}, p_\epsilon$) identifies an optimized way to resolve the batch \mathcal{D} : speedup is allowed by the knowledge of its expected multiplicity.

Expected running time depends on the BRA used but in general can be considered $O(p_\epsilon n)$: time is linear in the size of \mathcal{E} .

3.2.1 Estimate accuracy

In the original paper [3] there is no detailed analysis of the behavior of the algorithm but it is only shown the following fact: as n grows the estimator becomes more accurate.

Let J be an integer random variable which expresses the number of nodes in \mathcal{E} . Given a batch of size n , J is binomially distributed with parameter p_ϵ . It can be thought as the probability distribution to put j among n nodes in two bins choosing with probability p_ϵ the first one and $1 - p_\epsilon$ the other one. Therefore, we have the following:

1)

$$P(J = j|n) = \binom{n}{j} p_\epsilon^j (1 - p_\epsilon)^{n-j} \quad (3.4)$$

2)

$$E[J|n] = np_\epsilon \quad (3.5)$$

3)

$$\text{var}(J|n) = np_\epsilon(1 - p_\epsilon) \quad (3.6)$$

By applying Chebychev's Inequality (A.1), we have for any $\epsilon > 0$

$$P(|J - np_\epsilon| \geq \epsilon n | n) \leq \frac{p_\epsilon(1 - p_\epsilon)}{\epsilon^2 n} \quad (3.7)$$

Let \hat{N} be a real-valued random variable that expresses our estimate upon n . Then from (3.4) - (3.10):

1)

$$P(\hat{N} = n|n) = \binom{n}{j} p_\epsilon^j (1 - p_\epsilon)^{n-j} \quad \text{with} \quad \hat{n} = j/p_\epsilon, \quad 0 \leq j \leq n \quad (3.8)$$

2)

$$E[\hat{N}|n] = n \quad (3.9)$$

3)

$$P\left(\left|\frac{\hat{N}}{n} - 1\right| \geq \epsilon | n\right) \leq \frac{1 - p_\epsilon}{\epsilon^2 np_\epsilon} \quad (3.10)$$

3.3 Greenberg

Let, as usual, n be our batch size.

Basic Greenberg algorithm's strategy is to search for *a power of 2* that is close to n with high probability.

The probabilistic test is defined to look for \hat{n} which tries to satisfy:

$$\hat{n} \geq 2^i \approx n \quad (3.11)$$

Let each of the n conflicting stations either transmit or not transmit in accordance with whether the outcome of a biased binary coin is 0 or 1. The coin is biased to turn up 0 with probability 2^{-i} and 1 with complementary probability. Since the expected number of transmitters is $2^{-i}n$, having a conflict as event supports the hypothesis that $n \geq 2^i$.

Using this test repeatedly with $i = 1, 2, 3, \dots$ leads to the Greenberg *base 2 estimation algorithm*.

Each of the conflicting stations executes Algorithm (3), resulting in a string of collisions whose length determines \hat{n} .

As i increases, the probability that at most one node transmits increases monotonically and approaches 1 extremely rapidly as i increases past $\log_2 n$ so we expect i is close to $\log_2 n$.

Algorithm 3 BASIC GREENBERG

$i \leftarrow 0$

repeat

$i \leftarrow i + 1$

 choose to transmit with probability 2^{-i}

until no collision occurs

$\hat{n} \leftarrow 2^i$

The idea behind algorithm 3 appears to be quite simple: as the algorithm goes on the initial unknown batch (of size n) comes progressively sliced into smaller pieces. Only the nodes virtually inside the slice are allowed to transmit. Slices get thinner and thinner until at most one node is contained in a slice. Figure 3.3 intuitively tries to explain the idea.

Expected running time is $O(\log_2 n)$. In particular, since in the SLOTTED ALOHA model considered in the paper reader feedback is supposed to be transmitted at the end

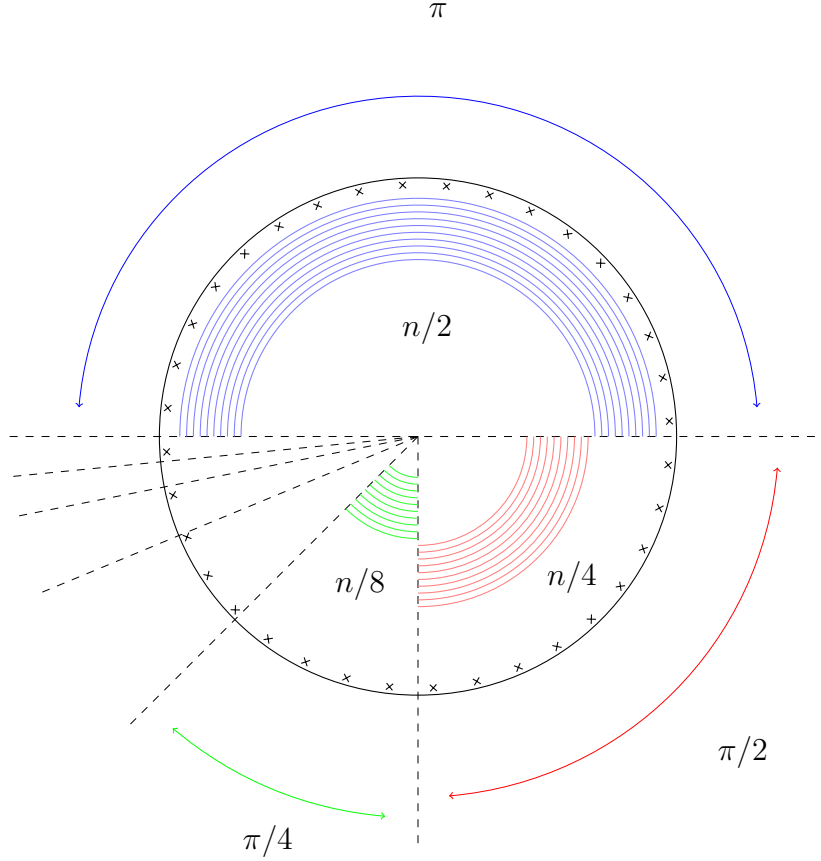


Figure 3.3: Visually nodes can be thought to be uniformly distributed on the circumference of a circle. By performing Greenberg's algorithm we go and analyze each time a smaller sector (in this case the half of the previous one) of the circle and find when a sector contains only 1 or no nodes. Not overlapping sectors are drawn to maintain the image simple but in general nodes gets redistributed to each step of the algorithm

of each transmission slot, expected running time can be expressed, in slot numbers, as $\approx 1 + \log_2 n$.

An important note is that the algorithm always involve all the nodes in the batch: in each stage of the algorithm each node has to take a choice if transmit or not. Each choice is independent of what the node did in the previous steps.

This is of great importance and allows \hat{n} to have bounded moments: it can be shown for large n that:

$$E[\hat{n}] \approx n\phi \quad (3.12)$$

$$E[\hat{n}^2] \approx n\Phi \quad (3.13)$$

where

$$\phi = \frac{1}{\log 2} \int_0^\infty e^{-x}(1+x) \prod_{k=1}^\infty (1 - e^{-2^k x}(1 + 2^k x)) x^{-2} dx = 0.91422 \dots \quad (3.14)$$

$$\Phi = \frac{1}{\log 2} \int_0^\infty e^{-x}(1+x) \prod_{k=1}^\infty (1 - e^{-2^k x}(1 + 2^k x)) x^{-3} dx = 1.23278 \dots \quad (3.15)$$

ϕ and Φ where obtained in [4] using advanced mathematical analysis supported by Mellin integral transform¹. In general ϕ and Φ depend on the size of the problem. We present Table 3.1 to provide an idea of the behavior of ϕ as function of n .

Table 3.1: Given a batch of size n the expected estimate applying base 2 Greenberg is $E[\hat{n}|n]$. The ratio $E[\hat{n}|n]/n$ monotonically decreases and gets stable at 0.9142. This shows that this estimate technique provide biased results.

| n | $E[\hat{n} n]$ | $E[\hat{n} n]/n$ |
|-------|----------------|------------------|
| 1 | 2.00 | 2.0000 |
| 2 | 2.56 | 1.2822 |
| 4 | 4.21 | 1.0533 |
| 8 | 7.89 | 0.9863 |
| 16 | 15.20 | 0.9498 |
| 32 | 29.82 | 0.9320 |
| 64 | 59.08 | 0.9231 |
| 128 | 117.59 | 0.9186 |
| 256 | 234.60 | 0.9164 |
| 512 | 468.64 | 0.9153 |
| 1024 | 936.71 | 0.9148 |
| 2048 | 1872.86 | 0.9145 |
| 4096 | 3745.14 | 0.9143 |
| 8192 | 7489.72 | 0.9143 |
| 16384 | 14978.86 | 0.9142 |
| 32768 | 29957.16 | 0.9142 |
| 65536 | 59913.74 | 0.9142 |

¹in this work we only report these as final results, please refer to the original paper to see how ϕ and Φ where obtained.

The fact that, for large n , $E[\hat{n}] \approx n\phi$ suggests treating $\hat{n}_+ = \hat{n}/\phi$ as a estimate of n .

Interestingly, a simple variant of the estimation algorithm has disastrous performance. Consider the algorithm in which each station involved in the initial collision transmits to the channel with probability $\frac{1}{2}$. If this causes another collision, then those that just transmitted again transmit with probability $\frac{1}{2}$. The others drop out. This continues, with the stations continuing to try to transmit always being a subset of those that just transmitted, until there is no collision. Take 2^i as the estimate of the multiplicity of conflict where i is the number of the steps until there is no collision. It can be shown that the second and all higher moments of this estimate are infinite.

3.3.1 base b variant

Using basic Algorithm 3, even though the expected value of \hat{n}_+ is quite close to n , \hat{n}_+ is likely to differ from n by a factor of 2. In the original work a small generalization of the base 2 algorithm is proposed to remedy this limit: providing an estimate whose mean is close to n but whose distribution peaks more sharply about the mean.

Simply it is suggested to use b instead of 2 as base, with $1 < b \leq 2$.

Algorithm 4 BASE b GREENBERG

```

 $i \leftarrow 0$ 
repeat
     $i \leftarrow i + 1$ 
    transmit with probability  $b^{-i}$ 
until no collision occurs
 $\hat{n}(b) \leftarrow 2^i$ 
 $\hat{n}_+(b) \leftarrow \hat{n}(b)/\phi(b)$ 

```

$\phi(b)$ corrects the bias of the estimator. $\phi(b)$ is the optimal correction when n is large. Looking at Table 3.2 you can notice how smaller b results in smaller $\phi(b)$. This means that b deeply biases the estimate: if $b' < b''$ then $E[\hat{n}(b')] < E[\hat{n}(b'')]$.

This is a result of the following fact: let i'' be the expected slot the base b'' algorithm will end up given a batch size n , then $i'' \leq \log_{b''} n$. Let i' be the same for b' . If $b' < b''$ then $b'^{i'} > b''^{i''}$ †

†This comes from experimental observations.

Table 3.2: Following table shows how ϕ and “Expected algorithm 4 cost in slots” vary for different b . Expected cost ($\lesssim \log_b n$) is expressed as a multiplicative factor for the basic Greenberg algorithm cost ($\lesssim \log_2 n$).

| b | $\phi(b)^a$ | Expected cost in slots-1 | |
|--------|------------------|--------------------------|-------------------|
| 2 | ≈ 0.9142 | $\lesssim 1$ | $\times \log_2 n$ |
| 1.1 | ≈ 0.3484 | $\lesssim 7.27$ | |
| 1.01 | ≈ 0.1960 | $\lesssim 69.66$ | |
| 1.001 | ≈ 0.1348 | $\lesssim 693.49$ | |
| 1.0001 | ≈ 0.1027 | $\lesssim 6931.81$ | |

^a Code used to compute $\phi(b)$ is provided in Appendix A.2

It can be shown [4] that, *for all n greater than some constant $n_0(b)$*

1.

$$\left| \frac{E[\hat{n}_+(b)]}{n} - 1 \right| < \epsilon(b) \quad (3.16)$$

2.

$$\frac{\sigma(\hat{n}_+(b))}{n} < \epsilon(b) \quad (3.17)$$

where $\epsilon(b) \rightarrow 0$ as $b \rightarrow 1$.

In other words when $b \rightarrow 1$ and n is large the estimate becomes unbiased and variance goes to 0: we have ideally a perfect estimator.

Our experimental results showed that this estimator is not so good for real life scenarios.

3.4 Window Based

Chapter 4

Initial batch size estimate

We investigated about a fast algorithm for multiplicity estimation.

4.1 Cidon Evaluation

We remember from section 3.2.1 that

$$P(J = j|n) = \binom{n}{j} p_\epsilon^j (1 - p_\epsilon)^{n-j}$$

and

$$\hat{n} = j/p$$

Note that in Alg. 2 (Cidon) we have p_ϵ *a priori* fixed since it is an input parameter of the algorithm. So J is a binomial distribution with parameters $B(n, p_\epsilon)$ and recalling (3.5) we get:

$$E[\hat{n}|n, p_\epsilon] = \frac{1}{p_\epsilon} E[j|n, p_\epsilon] = n, \quad \forall p_\epsilon \quad (4.1)$$

This shows that Cidon provides an unbiased estimator ($E[\hat{n}|n] = n$) independently from p_ϵ : p_ϵ influences only the variance of the estimator.

$$\begin{aligned} \text{var}(\hat{n}|n) &= E[\hat{n}^2|n] - E[\hat{n}|n]^2 \\ &= \frac{1}{p_\epsilon^2} E[j^2|n] - n^2 \\ &= \frac{np_\epsilon(1 - p_\epsilon) + n^2 p_\epsilon^2}{p_\epsilon^2} - n^2 \\ &= n \frac{(1 - p_\epsilon)}{p_\epsilon} \end{aligned} \quad (4.2)$$

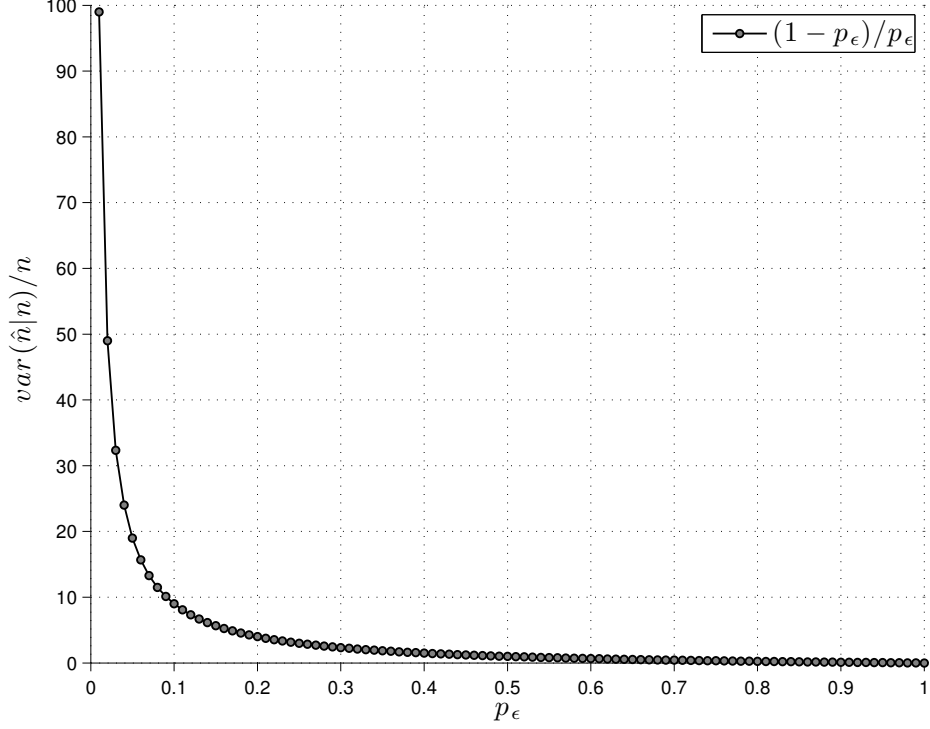


Figure 4.1: *Cidon*: estimate accuracy dramatically improves while $p_\epsilon \leq 0.1$.

Variance is strict monotonically decreasing in p_ϵ . Anyway it is difficult to establish in what measure an estimate can be considered accurate.

Given n , let $k \geq 1$ define the minimum required accuracy in the following way:

$$\frac{n}{k} \leq \hat{n} \leq kn \quad (4.3)$$

Let θ be the probability we require for constrains (4.3) to be satisfied.

If we set $\theta = 0.99$, we can find the minimum p_ϵ , ensuring the estimate to be within confidence interval (4.3), by solving the following problem.

$$\begin{aligned} P\left(\frac{n}{k} \leq \hat{n} \leq kn \mid k, n\right) &= P\left(\frac{n}{k} \leq j/p_\epsilon \leq kn \mid k, n, p_\epsilon\right) \\ &= P\left(\frac{np_\epsilon}{k} \leq j \leq knp_\epsilon \mid k, n, p_\epsilon\right) \end{aligned} \quad (4.4)$$

Probability in (4.4) is well behaved and expresses a constrain for j , which is a value assumed by J mentioned in (3.4). Since J assumes positive integer values we introduce rounding operations. In particular, rounding effect is non neglectible when $n \leq 200$.

$$f(k, n, p_\epsilon) = P\left(\left\lceil \frac{np_\epsilon}{k} \right\rceil \leq j \leq \lfloor knp_\epsilon \rfloor \mid k, n, p_\epsilon\right) \geq \theta \quad (4.5)$$

Fixed k , n and θ , p_ϵ can be found by numerically solving¹:

$$f(k, n, p_\epsilon) = \theta \quad (4.6)$$

Figure below shows p_ϵ in function of k for different batch sizes.

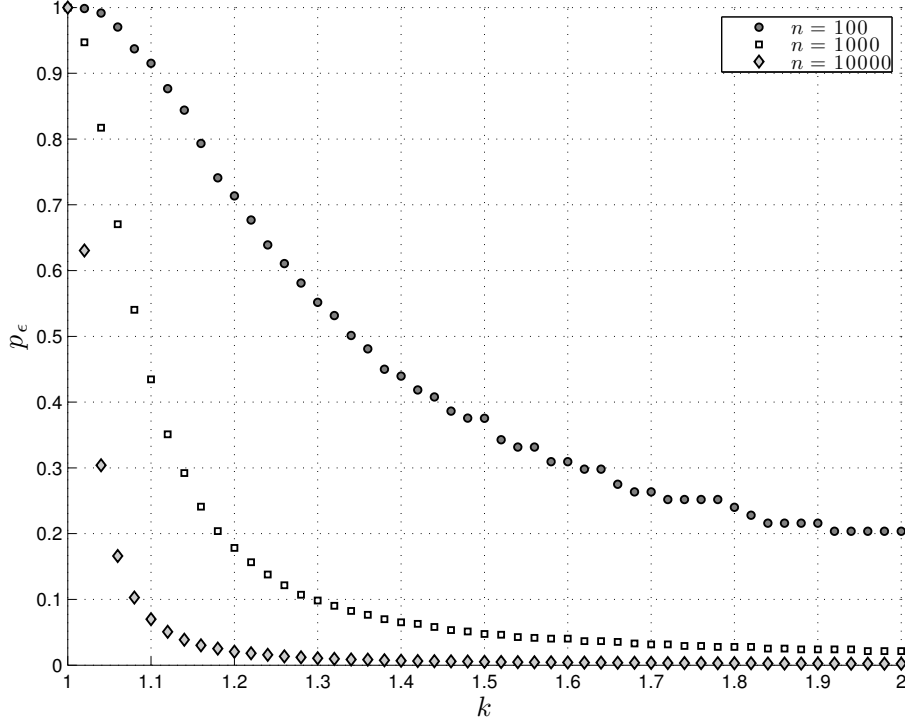


Figure 4.2: *Cidon*: Minimum p_ϵ required for accuracy k with $\theta = 0.99$. k step is 0.02

Figure 4.2 shows how the fraction of the initial batch to resolve for estimate to be within required confidence interval with high probability deeply depends on the size of the problem: smaller sizes require much higher p_ϵ .

At the same time, considering absolute cost in elapsed slots, Figure 4.3 shows that, for a wide range of k , the time required is quite independent of the size of the problem.

Time required by the largest considered n provides a bound for smaller ones.

Note that in Figure 4.3 an upper bound on the expected BRI time taken is plotted: this bound is not so tight for very small batches. With small batches BRAs performs better than what is reported.

¹in this work we used bisection method

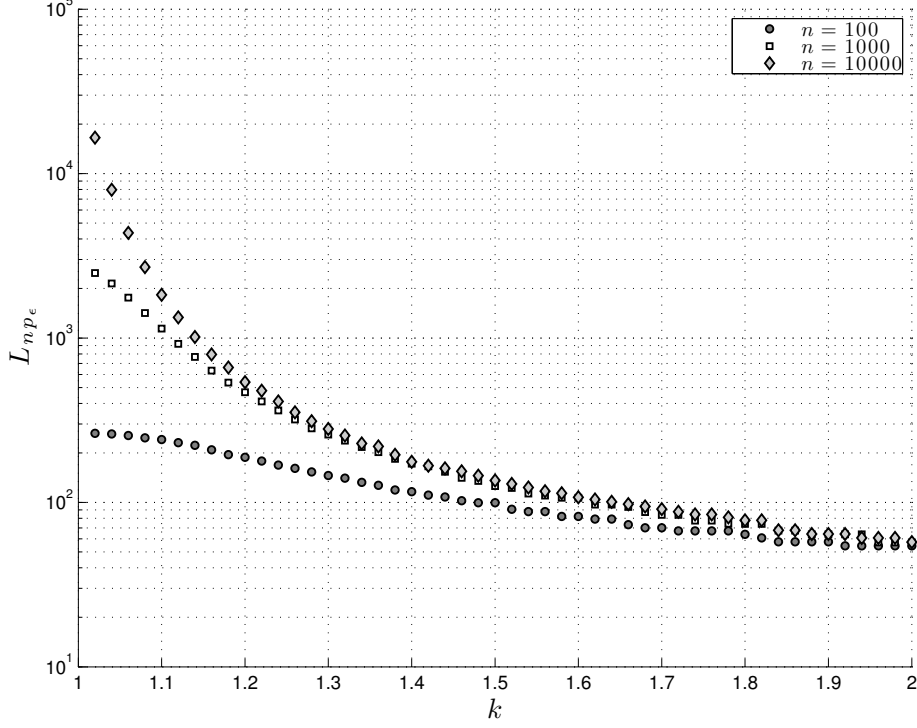


Figure 4.3: *Cidon*: Upper bounds on the expected time (in slots) required to achieve accuracy k with $\theta = 0.99$. k step is 0.02

4.2 Greenberg Evaluation

Given a current slot transmission probability p and a batch of size n we define respectively:

1. the probability to get an empty slot (no transmissions)

$$q_0(p, n) = (1 - p)^n \quad (4.7)$$

2. the probability to get a successful transmission (one transmission)

$$q_1(p, n) = np(1 - p)^{n-1} \quad (4.8)$$

3. the probability to get a collision (two or more transmissions)

$$q_{2+}(p, n) = 1 - q_0 - q_1 \quad (4.9)$$

In basic Greenberg (*Alg. 3*) each slot is associated with a different probability p . Naming each slot i starting with 1, 2, ..., we have:

$$p_i = p(i) = 2^i \quad (4.10)$$

Given n nodes, the probability to terminate algorithm 3 in slot i is given by:

$$f(n, i) = \prod_{k=1}^{i-1} q_{2+}(p_k, n) (q_0(p_i, n) + q_1(p_i, n)) \quad (4.11)$$

An overview of the behavior of $f(n, i)$ is presented in table A.2 on page 46.

$$\Pr(\hat{n} = 2^i | n) = f(n, i) \quad (4.12)$$

Following Figures 4.4 and 4.5 show how the distribution behave for small and large sizes. We note that, for any fixed n , the distribution is well behaved: initially it is monotonically increasing, then a monotonically decreasing part follows.

It turns out that, for batch sizes larger than 128, the distribution is “stable” in the sense that doubling the number of nodes produces a shift of 1 slot to the right but the values assumed are the same (see Figure 4.5).

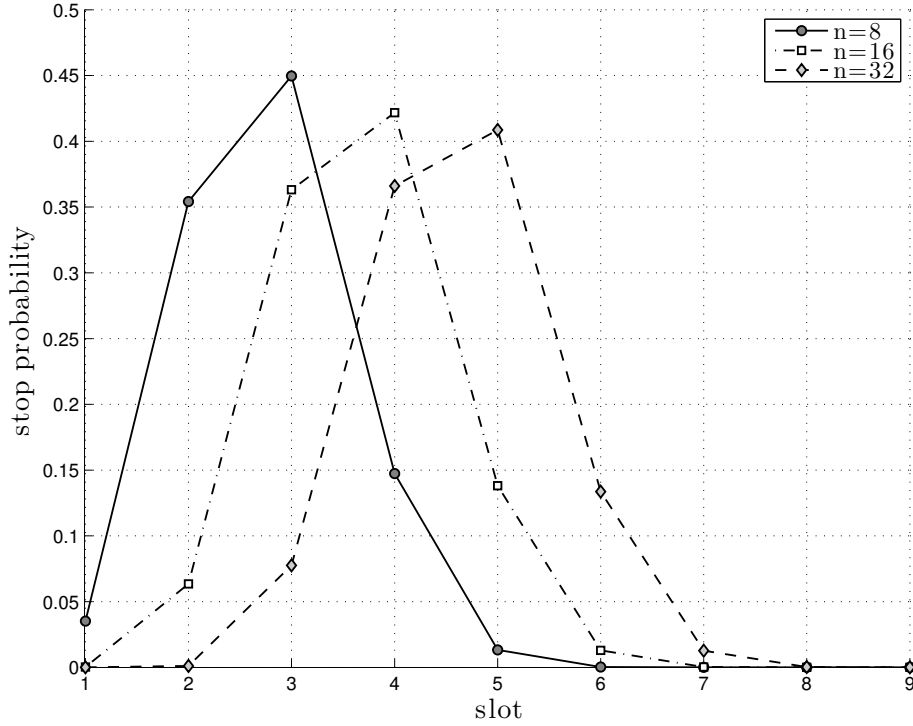


Figure 4.4: Basic Greenberg: small 2^k sizes distribution.

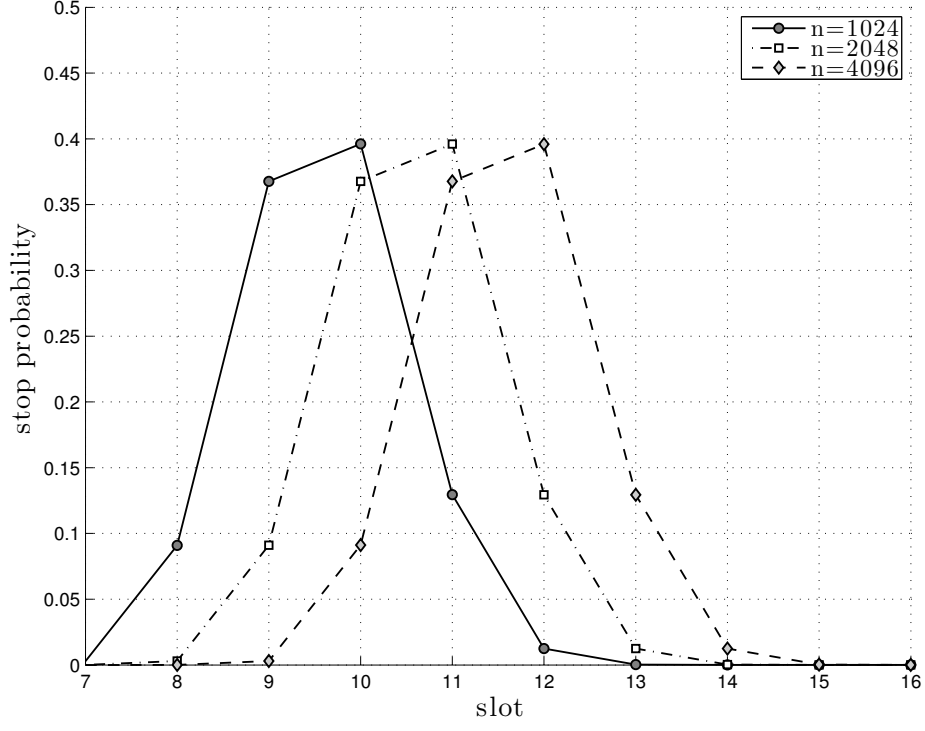


Figure 4.5: *Basic Greenberg*: large 2^k sizes distribution.

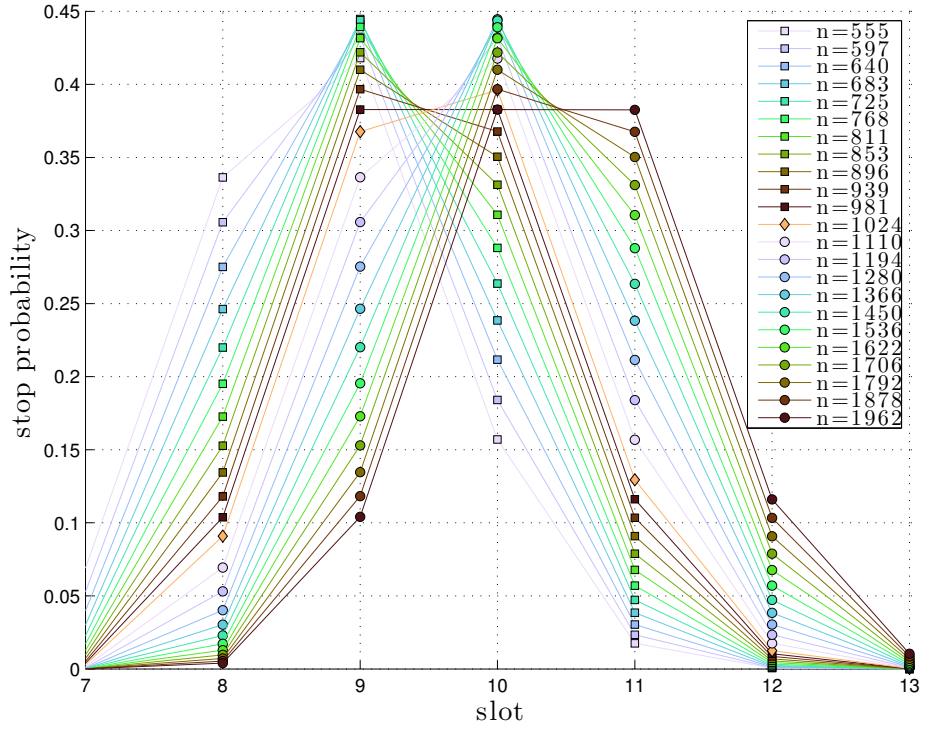


Figure 4.6: *Basic Greenberg*: general sizes distribution.

This is not only true for sizes power of two but for any size. Figure 4.6 shows the case where size n' has color c and size $2n'$ has, again, color c but a different marker: values are the same but shifted right. Interestingly the highest peaks are located in $n = 683$ and $n = 1366$.

4.2.1 base b Greenberg

4.2.2 Considerations

Greenberg method is really good from the point view of running cost since it is $O(\log_2 n)$ respect to the size n of the problem but it has also some non negligible drawbacks:

- a) estimation phase results in a sequence of colliding messages. These provides informations about the cardinality of the batch but do not help to solve an, even small, portion of the eventually following batch resolution problem and can not carry auxiliary infromations. An algorithm that allows to get an estimate while transmitting successfully messages would offer some advantages when the problem is not only the pure estimation but also a subsequent resolution.
- b) it does not allow to achieve arbitrary precision in the estimate.

In fact we have that:

- i. the estimate is, by construction, a power of 2. Only a small subset of batch sizes can be mapped without any error.
- ii. the end-up distribution is not sharp enough but it spans over a few slots: this is shown by Figure 4.5. The Figure shows that, for the examined batch sizes, fixed a problem of size n we have about:

- 0.02‰ estimate is $16n$;
- 3‰ estimate is $8n$;
- 1.2% estimate is $4n$;
- 12.9% estimate is $2n$;
- 39.6% estimate is n ;
- 36.8% estimate is $\frac{n}{2}$: perfect ✓;
- 9.1% estimate is $\frac{n}{4}$;
- 3 ‰ estimate is $\frac{n}{8}$;
- 0.02‰ estimate is $\frac{n}{16}$;

It is difficult to discriminate between n and $\frac{n}{2}$

4.3 Modified Greenberg with MLE

Chapter 5

Comparison

Appendix A

A.1 Probability

sezione provvisoria

A.1.1 Chebyshev's inequality

Let X be a *random variable* with expected value μ and finite variance σ^2 . Then for any real number $k > 0$,

$$\Pr(|X - \mu| \geq k) \leq \frac{\sigma^2}{k^2} \quad (\text{A.1})$$

A.1.2 Binomial Distribution

$B(n, p)$

Poisson Approximation

The binomial distribution converges towards the Poisson distribution as the number of trials goes to infinity while the product np remains fixed. Therefore the Poisson distribution with parameter $\lambda = np$ can be used as an approximation to $B(n, p)$ of the binomial distribution if n is sufficiently large and p is sufficiently small. According to two rules of thumb, this approximation is good if $n \geq 20$ and $p \leq 0.05$, or if $n \geq 100$ and $np \leq 10$.

Normal Approximation

If n is large enough, then the skew of the distribution is not too great. In this case, if a suitable continuity correction is used, then an excellent approximation to $B(n, p)$ is given by the normal distribution $\mathcal{N}(np, np(1 - p))$

The approximation generally improves as n increases and is better when p is not near to

0 or 1. Various rules of thumb may be used to decide whether n is large enough, and p is far enough from the extremes of zero or unity: One rule is that both np and $n(1 - p)$ must be greater than 5. However, the specific number varies from source to source, and depends on how good an approximation one wants; some sources give 10.

oppure dal libro $np(1 - p) \geq 10$.

A.1.3 Poisson Distribution

A.1.4 Normal Distribution

$\mathcal{N}(\mu, \sigma^2)$

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp -\frac{(x - \mu)^2}{2\sigma^2} \quad (\text{A.2})$$

A.2 Greenberg bounded m -moments

In general for base b greenberg algorithm the first and second moments are bounded by:

$$\phi(b) = \frac{1}{\log b} \int_0^\infty e^{-x}(1+x) \prod_{k=1}^\infty (1 - e^{-b^k x}(1 + b^k x)) x^{-2} dx \quad (\text{A.3})$$

$$\Phi(b) = \frac{1}{\log b} \int_0^\infty e^{-x}(1+x) \prod_{k=1}^\infty (1 - e^{-b^k x}(1 + b^k x)) x^{-3} dx \quad (\text{A.4})$$

$\phi(b)$ was computed using the code below. Even if the integral is improper the integrand function goes fast to 0 and so the product does when k grows. We found that considering interval (0,40) for numerical integration provided good results.

matlab/Greenberg_base_b/phi/calculatephi.m

```

1 %sample script to calculate phi
2
3 clc;
4 clear all;
5 close all;
6
7 b=2 % 1<b<=2
8 phi=quadl(@f4(x,b),0,40,1.e-9)/log(b) ;
9 phi
10
11 % Sample output

```

```

12 %
13 % b =
14 %     2
15 % phi =
16 %     0.914217701315935

```

matlab/Greenberg_base_b/phi/f4.m

```

1 function y=f4(x,a)
2
3 % y=f4(x,a)
4 %
5 % input:
6 %     a: base
7 %     x: x-point
8 %
9 % implements the function to integrate to calculate phi
10
11 y=exp(-x).*(1+x).*f3(a,x).*x.^-2;

```

matlab/Greenberg_base_b/phi/f3.m

```

1 function p=f3(a,x)
2
3 % p = f3(a,x)
4 %
5 % compute the infinite product stopping when the terms converge to 1
6
7 l=length(x);
8 p=zeros(1,l);
9
10 for k=1:l
11     do=true;
12     i=1;
13     %valore al passo precedente
14     y0=f2(a,x(k),1);
15     v0=1;
16     p(k)=y0;
17     while (do)
18         v1=bitshift(1,i);
19         %valore al passo attuale
20         y1=f2(a,x(k),v1);
21         if (y0==y1)
22             % allora converge a 1
23             do=false;
24         else
25             for ii=v0+1:v1
26                 p(k)=p(k).*f2(a,x(k),ii);
27             end

```

```

28         y0=y1;
29         v0=v1;
30     end
31     i=i+1;
32 end
33 end

```

matlab/Greenberg_base_b/phi/f2.m

```

1 function y=f2(a,x,k)
2
3 % y = f2(a,x,k)
4 %
5 % a term inside the product
6
7 c=a.^k;
8 y=(1-exp(-c.*x)).*(1+c.*x);

```

A.3 CBT Estimate Experimental Distribution

Following tables A.1 shows the behavior of CBT Algorithm (section 3.1) for estimation. Simulation was implemented in matlab. The resulting distribution of \hat{n} fixed n is the result of averaging 100 000 runs of CBT Algorithm applied on uniformly random generated nodes ID batches.

Table A.1: Experimentally computed CBT Estimate Distributon. Table 1/3

| n | \hat{n} : | 2 | 4 | 8 | 16 | 32 | 64 | 128 | 256 | 512 | 1024 | 2048 |
|-------|-------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 2 | | 0.499 | 0.253 | 0.125 | 0.061 | 0.031 | 0.015 | 0.007 | 0.004 | 0.002 | 9e-04 | 4e-04 |
| 4 | | | 0.189 | 0.303 | 0.225 | 0.133 | 0.072 | 0.038 | 0.020 | 0.010 | 0.005 | 0.002 |
| 8 | | | 0.055 | 0.212 | 0.261 | 0.201 | 0.126 | 0.071 | 0.037 | 0.019 | 0.009 | 0.005 |
| 16 | | | 8e-04 | 0.070 | 0.209 | 0.252 | 0.197 | 0.125 | 0.070 | 0.038 | 0.019 | 0.010 |
| 32 | | | | 0.003 | 0.075 | 0.213 | 0.249 | 0.195 | 0.123 | 0.069 | 0.037 | 0.018 |
| 64 | | | | | 0.004 | 0.077 | 0.208 | 0.250 | 0.193 | 0.124 | 0.069 | 0.037 |
| 128 | | | | | | 0.005 | 0.081 | 0.208 | 0.247 | 0.191 | 0.123 | 0.069 |
| 256 | | | | | | 2e-05 | 0.006 | 0.079 | 0.209 | 0.246 | 0.193 | 0.123 |
| 512 | | | | | | | | 0.005 | 0.081 | 0.207 | 0.245 | 0.193 |
| 1024 | | | | | | | | | 0.005 | 0.080 | 0.208 | 0.245 |
| 2048 | | | | | | | | | 2e-05 | 0.005 | 0.080 | 0.209 |
| 4096 | | | | | | | | | | 1e-05 | 0.006 | 0.082 |
| 8192 | | | | | | | | | | | 1e-05 | 0.006 |
| 16384 | | | | | | | | | | | | 2e-05 |
| 32768 | | | | | | | | | | | | |

Table A.1: Experimentally computed CBT Estimate Distributon. Table 2/3

| n | \hat{n} : | 4096 | 8192 | 16384 | 32768 | 2^{16} | 2^{17} | 2^{18} | 2^{19} | 2^{20} | 2^{21} | 2^{22} |
|-------|-------------|-------|-------|-------|-------|----------|----------|----------|----------|----------|----------|----------|
| 2 | | 2e-04 | 1e-04 | 1e-04 | | | | 1e-05 | | | | |
| 4 | | 0.001 | 5e-04 | 3e-04 | 1e-04 | 6e-05 | 4e-05 | | 2e-05 | 1e-05 | | |
| 8 | | 0.002 | 0.001 | 6e-04 | 3e-04 | 9e-05 | 8e-05 | 4e-05 | 1e-05 | | | |
| 16 | | 0.005 | 0.003 | 0.001 | 6e-04 | 3e-04 | 2e-04 | 6e-05 | 2e-05 | 2e-05 | | |
| 32 | | 0.009 | 0.005 | 0.003 | 0.001 | 6e-04 | 3e-04 | 1e-04 | 1e-04 | 6e-05 | 1e-05 | 1e-05 |
| 64 | | 0.019 | 0.009 | 0.005 | 0.002 | 0.001 | 7e-04 | 3e-04 | 7e-05 | 4e-05 | | 2e-05 |
| 128 | | 0.037 | 0.019 | 0.010 | 0.005 | 0.003 | 0.001 | 5e-04 | 4e-04 | 2e-04 | 5e-05 | 4e-05 |
| 256 | | 0.068 | 0.038 | 0.019 | 0.009 | 0.005 | 0.002 | 0.001 | 6e-04 | 3e-04 | 6e-05 | 8e-05 |
| 512 | | 0.123 | 0.071 | 0.037 | 0.019 | 0.010 | 0.005 | 0.002 | 0.001 | 6e-04 | 3e-04 | 2e-04 |
| 1024 | | 0.193 | 0.122 | 0.070 | 0.037 | 0.019 | 0.010 | 0.005 | 0.002 | 0.001 | 6e-04 | 2e-04 |
| 2048 | | 0.246 | 0.194 | 0.123 | 0.068 | 0.037 | 0.019 | 0.010 | 0.005 | 0.002 | 0.001 | 6e-04 |
| 4096 | | 0.210 | 0.246 | 0.193 | 0.121 | 0.068 | 0.037 | 0.019 | 0.009 | 0.004 | 0.003 | 0.001 |
| 8192 | | 0.080 | 0.208 | 0.247 | 0.192 | 0.123 | 0.070 | 0.037 | 0.019 | 0.009 | 0.005 | 0.002 |
| 16384 | | 0.006 | 0.080 | 0.208 | 0.247 | 0.192 | 0.123 | 0.069 | 0.037 | 0.019 | 0.010 | 0.005 |
| 32768 | | | 0.006 | 0.079 | 0.209 | 0.248 | 0.194 | 0.122 | 0.069 | 0.036 | 0.019 | 0.010 |

Table A.1: Experimentally computed CBT Estimate Distributon. Table 3/3

| n | \hat{n} : | 2^{23} | 2^{24} | 2^{25} | 2^{26} | 2^{27} | 2^{28} | 2^{29} | 2^{30} | 2^{31} | 2^{32} |
|-------|-------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| 2 | | | | | | | | | | | |
| 4 | | | | | | | | | | | |
| 8 | | | | | | | | | | | |
| 16 | | | | | | | | | | | |
| 32 | | 1e-05 | | | | | | | | | |
| 64 | | 2e-05 | | | | 1e-05 | | | | | |
| 128 | | 4e-05 | | 1e-05 | | | | | | | |
| 256 | | 4e-05 | 1e-05 | | 2e-05 | | | 1e-05 | | | |
| 512 | | 7e-05 | 2e-05 | 1e-05 | 3e-05 | 1e-05 | | | | | |
| 1024 | | 2e-04 | 1e-04 | 4e-05 | | 2e-05 | 1e-05 | | | | |
| 2048 | | 3e-04 | 1e-04 | 3e-05 | 3e-05 | 3e-05 | 3e-05 | | | | |
| 4096 | | 6e-04 | 3e-04 | 9e-05 | 7e-05 | 1e-05 | | | | | |
| 8192 | | 0.001 | 8e-04 | 3e-04 | 2e-04 | 8e-05 | 7e-05 | 2e-05 | 3e-05 | 1e-05 | |
| 16384 | | 0.002 | 0.001 | 6e-04 | 3e-04 | 1e-04 | 1e-04 | 4e-05 | | | |
| 32768 | | 0.005 | 0.002 | 0.001 | 6e-04 | 3e-04 | 2e-04 | 1e-04 | 1e-05 | 2e-05 | 1e-05 |

matlab/CBT/cbtsimpletest.m

```

1 % Marco Bettiol - 586580 - BATCH SIZE ESTIMATE
2 %
3 % CBT Simple Test
4 %
5 % This script implements a simulation of the estimate obtained
6 % using CBT in a batch of size n.
7 %
8 % Nodes are initially uniformly picked-up in the interval [0,1)
9
10
11 clear all;
12 close all;
13 clc;
14
15 n=16; % batch size
16 disp(['Size : ' int2str(n)]);
17
18 nodes=rand(n,1);
19 % virtual node with value 1 to get easier search algorithm
20 % among the nodes
21
22 % asc sorting

```

```

23 nodes=[sort(nodes); 1];
24
25 if (n<2)
26     error('BRA must start with a collision');
27 end
28 % CBT Simulation
29
30 % true if we got a success in the last transmission
31 lastwassuccess=false;
32 %false to end CBT
33 waitforconsecutive=true;
34
35 imax=length(nodes); %index of the first node in the batch
36 imin=1; % index of the first node in the batch
37 xmin=0; % starting interval [0,1/2)
38 xlen=1/2; % we suppose a collision already occurred.
39
40 while (waitforconsecutive)
41     [e,imin,imax]=cbtsplit(nodes,imin,imax,xmin,xlen);
42     % update next analyzed interval
43
44     if (e==1)
45         xmin=xmin+xlen;
46         %xlen=xlen;
47     elseif (e==0)
48         xmin=xmin+xlen;
49         xlen=xlen/2;
50     else
51         %xmin=xmin;
52         xlen=xlen/2;
53     end
54     if (lastwassuccess==true && e==1)
55         disp(' ');
56         disp('CBT completed :');
57         disp(['Estimate : ' num2str(1/xlen)]);
58         disp(['Last node transmitting : ' int2str(imin-1)]);
59         waitforconsecutive=false;
60     end
61     if (e==1)
62         lastwassuccess=true;
63     else
64         lastwassuccess=false;
65     end
66 end
67
68 % DEBUG
69 % estimate is given by the first serie of descending differences in the
70 % nodes ID's
71 dif=-1*ones(n-1,1); %negative init
72 for i=1:n-1
73     dif(i)=nodes(i+1)-nodes(i);
74 end
75
76 nodes

```

matlab/CBT/cbtsplit.m

```

1 % Marco Bettiol - 586580 - BATCH SIZE ESTIMATE
2
3 function [e,imin,imax]=cbtsplit(nodes,imin,imax,xmin,xlen)
4
5 %
6 % CBT BATCHSPLIT
7 %
8 % [e,imin,imax]=cbtsplit(nodes,imin,imax,xmin,xlen)
9 %
10 % Finds the nodes possibly enabled in the future conflicting set given the
11 % current enabled interval [xmin,xmin+xlen) and establish the event type
12 % for the current enabled interval
13 %
14 % Input:
15 %
16 % nodes : asc ordered vector of the nodes
17 % imin   : index of the first node that collided
18 % imax   : index of the first node in the sleeping set
19 % xmin   : lower bound of the new enabled interval
20 % xmax   : higher bound of the new enabled interval
21 %
22 % Output:
23 % e      : event obtained
24 % imin   : new index of the first node that collided
25 % imax   : new index of the first node in the sleeping set
26
27 xmax=xmin+xlen;
28
29 % idle slot happens when imin is greater than current max allowed value.
30 % Future set of nodes to analyze do not change
31 if (nodes(imin)>=xmax)
32     e=0;
33     return;
34 end
35
36 % this is always false by algorithm construction
37 % used to verify a trivial condition
38 %while (nodes(imin)<xmin)
39 %     imin=imin+1;
40 %end
41
42 % if event is a success
43 if (nodes(imin)<xmax && nodes(imin+1)>=xmax)
44     e=1;
45     imin=imin+1;
46 else
47 % if event is collision
48 % update the next enabled set

```

```

49     e=2;
50     while ((imax-1)~=0 && xmax<nodes(imax-1))
51         imax=imax-1;
52     end
53 end

```

matlab/CBT/cbtfulltest.m

```

1 % Marco Bettiol - 586580 - BATCH SIZE ESTIMATE
2 %
3 % CBT Full Test
4 %
5 % Estimate distributions obtained with CBT fixed different n
6 %
7 % Based on cbtsimpletest code
8
9 clear all;
10 close all;
11 clc;
12
13 % input
14 logn_max=15;
15 c=100000;
16
17 % generate the test batch size
18 x=1:logn_max;
19 testsizes=2.^x;
20
21 % resulting estimate distribution
22 % ED(log2(batch size), log2(estimate batch size));
23
24 ED=zeros(length(testsizes),length(testsizes)+40);
25
26 for i=1:length(testsizes)
27     n=testsizes(i);
28     disp(['Testing size : ' int2str(n)]);
29     if (n<2)
30         error('BRA must start with a collision');
31     end
32     for ii=1:c
33         %generate the batch
34         nodes=rand(n,1);
35         nodes=[sort(nodes); 1];
36         % CBT Estimate Simulation
37
38         % true if we got a success in the last transmission
39         lastwassuccess=false;
40         %false to end CBT
41         waitforconsecutive=true;
42
43         imax=length(nodes); %index of the first node in the batch
44         imin=1; % index of the first node in the batch

```

```

45     xmin=0;      % starting interval [0,1/2)
46     xlen=1/2;    % we suppose a collision already occurred.
47     l=1;         % current level in the tree
48
49     while (waitforconsecutive)
50         [e,imin,imax]=cbtsplit(nodes,imin,imax,xmin,xlen);
51         if (e==1)
52             xmin=xmin+xlen;
53         elseif (e==0)
54             xmin=xmin+xlen;
55             xlen=xlen/2;
56             l=l+1;
57         else
58             xlen=xlen/2;
59             l=l+1;
60         end
61         if (lastwassuccess==true && e==1)
62             waitforconsecutive=false;
63         end
64         if (e==1)
65             lastwassuccess=true;
66         else
67             lastwassuccess=false;
68         end
69     end
70     ED(i,l)=ED(i,l)+1;
71 end
72 end

```

A.4 Greenberg Estimate Distribution

In following table A.2 we report how the end up probability (equation 4.11) is distributed among slots given a batch of size n . Column “ n ” lists the considered batch sizes. \hat{n} is the resulting estimation (without corrections) when ending up in the underneath slot.

For sake of simplicity considered values are all powers of 2.

Datas presented were post-processed to become more accessible:

- values above 10^{-3} are reported in format (`'%1.3f'`);
- values below 10^{-12} are not presented since are tight close to 0.
- other values are presented in exponential notation and rounded to the first meaningful digit (`'%1.e'`)

| n | \hat{n} | 1 | 2 | 4 | 8 | 16 | 32 | 64 | 128 | 256 | 512 | 1024 | 2048 | 4096 | 8192 | 16384 | 32768 | 65536 |
|------|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|------|------|------|-------|-------|-------|
| n | slot: | 1 | 2 | 4 | 8 | 16 | 32 | 64 | 128 | 256 | 512 | 1024 | 2048 | 4096 | 8192 | 16384 | 32768 | 65536 |
| 1 | 1.000 | | | | | | | | | | | | | | | | | |
| 2 | 0.750 | 0.234 | 0.015 | 2e-04 | 1e-06 | 9e-10 | | | | | | | | | | | | |
| 4 | 0.312 | 0.508 | 0.166 | 0.014 | 3e-04 | 2e-06 | 2e-09 | | | | | | | | | | | |
| 8 | 0.035 | 0.354 | 0.450 | 0.147 | 0.013 | 3e-04 | 2e-06 | 4e-09 | 1e-12 | | | | | | | | | |
| 16 | 3e-04 | 0.063 | 0.363 | 0.422 | 0.138 | 0.013 | 3e-04 | 2e-06 | 4e-09 | 2e-12 | | | | | | | | |
| 32 | 8e-09 | 0.001 | 0.078 | 0.366 | 0.409 | 0.134 | 0.013 | 3e-04 | 2e-06 | 4e-09 | 2e-12 | | | | | | | |
| 64 | 2e-07 | 0.002 | 0.084 | 0.367 | 0.402 | 0.131 | 0.013 | 3e-04 | 2e-06 | 4e-09 | 2e-12 | | | | | | | |
| 128 | 7e-07 | 0.002 | 0.088 | 0.367 | 0.399 | 0.130 | 0.013 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | | |
| 256 | 1e-06 | 0.003 | 0.090 | 0.368 | 0.397 | 0.130 | 0.013 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | | |
| 512 | 2e-06 | 0.003 | 0.090 | 0.368 | 0.397 | 0.130 | 0.012 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | | |
| 1024 | 2e-06 | 0.003 | 0.091 | 0.368 | 0.396 | 0.129 | 0.012 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | | |

| n | \hat{n} | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
|-------|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----|----|----|----|----|----|
| n | slot: | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
| 2048 | 2e-06 | 0.003 | 0.091 | 0.368 | 0.396 | 0.129 | 0.012 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | |
| 4096 | 2e-06 | 0.003 | 0.091 | 0.368 | 0.396 | 0.129 | 0.012 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | |
| 8192 | 2e-06 | 0.003 | 0.091 | 0.368 | 0.396 | 0.129 | 0.012 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | |
| 16384 | 2e-06 | 0.003 | 0.091 | 0.368 | 0.396 | 0.129 | 0.012 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | |
| 32768 | 2e-06 | 0.003 | 0.091 | 0.368 | 0.396 | 0.129 | 0.012 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | |
| 65536 | 2e-06 | 0.003 | 0.091 | 0.368 | 0.396 | 0.129 | 0.012 | 3e-04 | 2e-06 | 5e-09 | 2e-12 | | | | | | |

Table A.2: Analytically computed basic Greenberg Estimate Distribution

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