# Scalable Logging Algorithm for in-Memory DBMS

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**Abstract**

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## 1 Introduction

As the world becomes more technology-oriented, the amount of data that is being stored and accessed has multiplied. From millions of users on Facebook to police records, the amount and complexity of data in virtual storage has incremented drastically. This growth has led to the study of **big data**, a term used for data sets that are too large and complex for traditional data processing methods. These large data sets are being analyzed in database management systems (DBMS). DBMS can be categorized into Online Transaction Processing (OLTP) and Online Analytical Processing (OLAP). OLTP databases are the main target of this paper and are characterized by a large number of short online transactions, such as bank transactions, flight ticket reservations, or hotel room bookings. OLAP, on the other hand, involves longer and more complex transactions such as business intelligence and data mining.

OLTP databases contain large amounts of important information. In order to preserve the information stored in the database in case of crashes, it is necessary to find a way to ensure the **durability** of the system. For this to happen, all of the data must be put on non-volatile storage, or logged onto the disk. The most efficient way to put these large amounts of data onto the disk is still debated because there are many different ways to accomplish the task.

One of the first and most well-known algorithms designed for the logging process was the Algorithm for Recovery and Isolation Exploiting Semantics (AIRES). In this algorithm, trasactions are logged sequentially, with one transaction waiting until all others before it are comitted before it commits. More details on the serial logging algorithm can be found in section 2. With the introduction of new technologies, however, multi-core and multi-server system have become more prevalent. These new systems render the AIRES algorithm obsolete as we are no longer limited to using only one thread in the logging process, which can be a bottleneck as the number of transactions handled by the logger increases dramatically.

This means that serial logging will no longer be useful in the future and new algorithms will be neccessary.

The goal of this paper is to solve this problem and generate a new logging algorithm that is faster and more efficient on a system with a multi-cores and multi-servers. The two algorithms that are presented in this paper are batch logging and parallel logging. In batch logging BRIEFLY EXPLAIN BATCH LOGGING. In parallel logging, we track the dependency between different transactions, which allows us to decide whether to log independently or serially; multiple threads are employed simultaneously with their respective loggers and log files.

The serial logging, batch logging, and parallel logging algorithms were implemented and then tested to determine the effiecieny of each.

# 2 Serial Logging

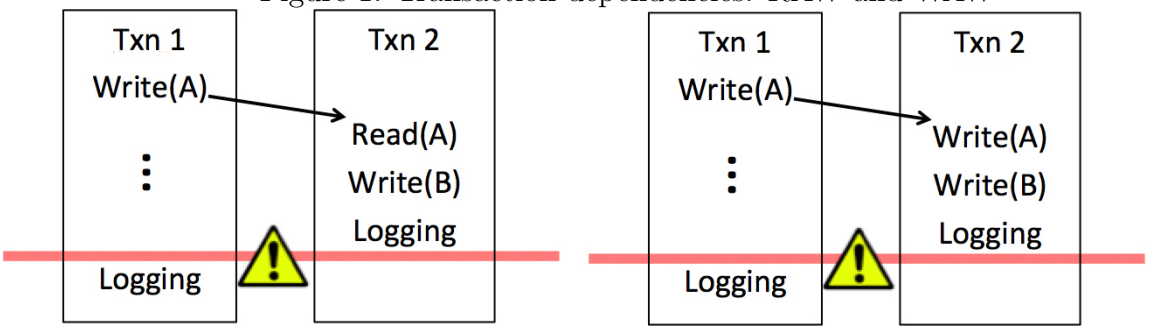
The state-of-the-art algorithm for serial logging is ARIES. In ARIES, each log record consists of one modified data tuple and the name of the transaction that modifies the tuple. It is assigned a log sequence number in ascending order. The log records are first pushed to volatile storage and then flushed to nonvolatile storage after the transaction is committed. Two data structures are maintained: the Dirty Page Table and the Transaction Table. The DPT keeps track of all the changes made to the database that have not been flushed to the disk, and the transaction table records all the transactions that are currently running in the system. During the recovery process, the system first recovers and updates the dirty page table and the transaction table, then recovers the system to the state immediately before the crash, and finally undoes all the transactions that have not been committed.

In our implementation of ARIES, we simplified the algorithm such that each transaction is logged together and corresponds to one unique LSN. Each transaction goes to log only after it is committed. This makes the dirty page table unnecessary, and we do not need to undo during the recovery process because only the committed transactions are reflected in stable storage.

A key insight of logging is that we need to maintain the dependency between different transactions. For example, in the following case on the left, Transaction 1 writes to tuple A and Transaction 2 read tuple A. If Transaction 2 is logged before the system crash whereas Transaction 1 is not, during the recovery processs, Transaction 2 will be reading the wrong data. Hence, Transaction 2 must go to log after Transaction 1 has already been logged.
The above type of transaction dependency is called read-after-write (RAW). In general, there are four types of transaction dependencies:

- Read-after-read dependency (RAR)
- Read-after-write dependency (RAW)
- Write-after-read dependency (WAR)
- Write-after-write dependency (WAW)

Figure 1: Transaction dependencies: RAW and WAW




RAR is equivalent to no dependency since no changes are made to the database. RAW has been discussed above, and WAW has to be maintained because in the example on the right, during recovery, transaction 2 will overwrite a phantom value of tuple A that cannot be tracked down in the system. Therefore, the reading transaction (2) should go to log after the writing transaction (1).

Since it is necessary to maintain different types of dependencies between pairs of transactions, the serial logging algorithm assumes that all dependencies have to be maintained and therefore logs the transactions one by one in sequential order. Our paper argues that this viewpoint is too conservative, and we propose the parallel algorithm, where we track down the types of transaction dependency to minimize the number of dependencies that we need to maintain. This involves a discussion of the WAR dependency. For more details, please refer to the parallel logging section.

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To be able to effectively compare serial logging to batch logging and parallel logging, however, the most effecient version of serial logging that is being used must be implemented. One of the optimizations for serial logging that was implemented is depicted in figure 2, where S stands for start of logging for a transaction and F stands for the end of logging for that transaction

In the standard version of serial logging without optimization, one transaction must finish committing before the next trasaction can even begin logging. This is insured by holding a lock for the entirety of the first transaction. In the optimized version of serial logging, however, the first transaction only holds the lock for the very beginning of the transaction to prevent any conflicts from occurring but still minimizing the time a lock is held for. The total run time is depicted as the the time from the start of the first transaction to the end of the third transaction, which is clearly shorter in the optimized version in comparison with the non optimzied version.

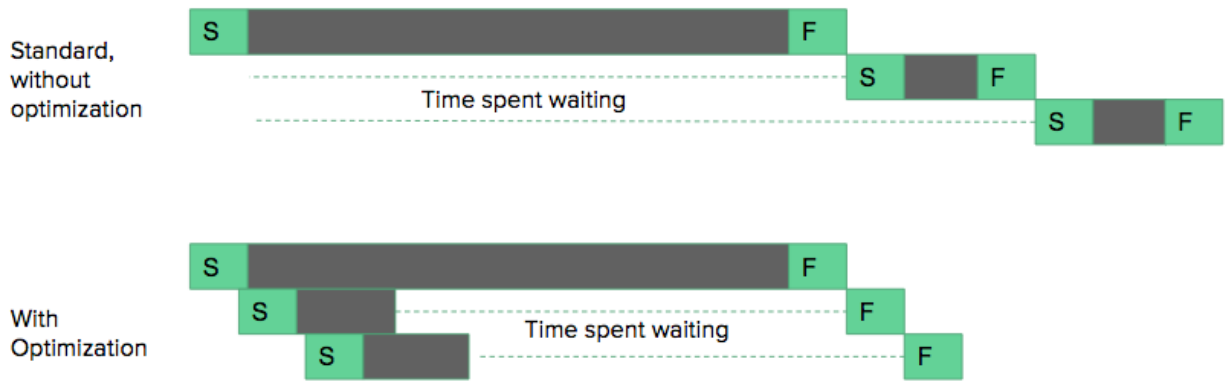
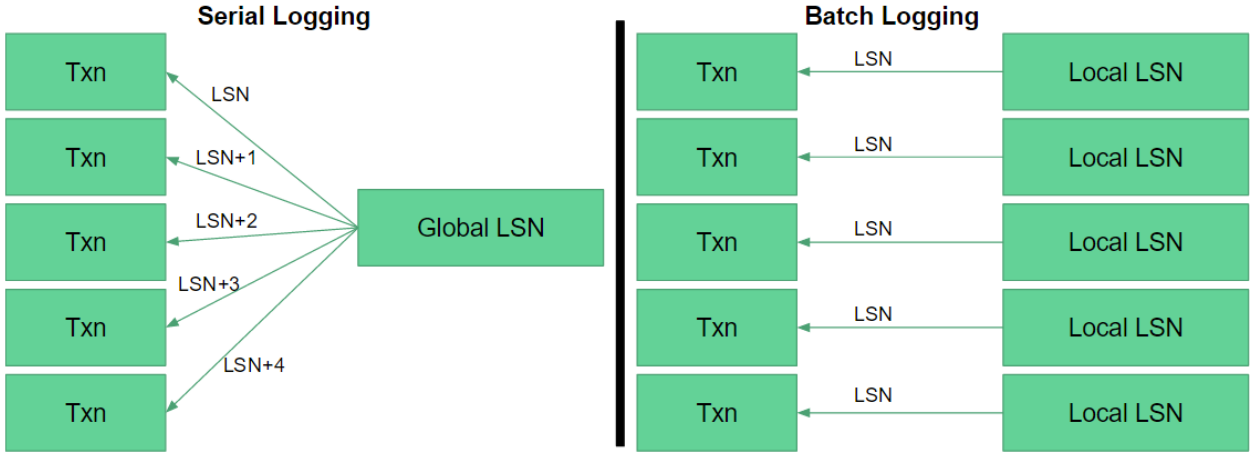



Figure 2: Serial Logging Optimization

# 3 Batch Logging

In serial logging, all transactions must obtain an unique and monotonically increasing LSN from the global LSN variable. This become problematic when there are many transactions occurring at the same time because they all access the same variable and thus create a bottleneck. In batch logging, this problem is solved by having multiple loggers with their individual and independent local LSNs. Transactions are evenly distributed to the loggers and each transaction can now take their LSN from the local LSN of their respective loggers. This eliminates the need for a global LSN and thus removes its inherent bottleneck. With

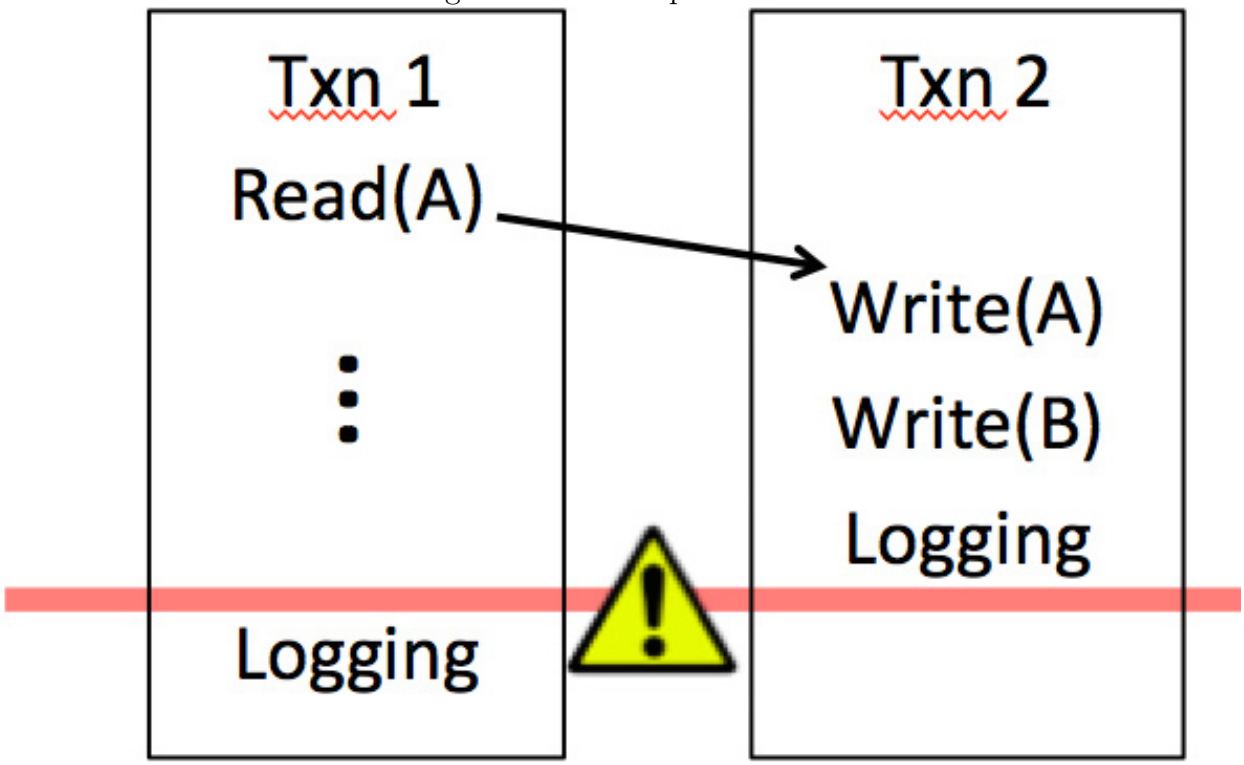
Figure 3: Serial logging versus Batch logging




multiple local loggers and their local LSNs, it must be assumed that there are dependencies between the loggers because it cannot be determined otherwise due to the lack of a global serial order, as was present in serial logging with the global LSN. This means that all loggers must sync after a certain interval before they can return to the user, causing a increase in latency compared to serial logging.

In our implementation, we handle the syncing of loggers by flushing all log buffers to

Figure 4: WAR dependencies




disk as soon as one becomes full. A bit vector is used to communicate between the loggers, where the index of the bit corresponds to the number of the logger and the logger flushes if its bit is 1. When a logger fills up its buffer, it changes all bits of the vector to be 1 to signal all other loggers to flush their buffers too. Each logger checks the bit vector upon receiving a transaction, and if their respective bit is 1, then the logger flushes and toggles its bit to 0 before placing the newly received transaction into its buffer.

# 4 Parallel Logging

Parallel logging uses multiple loggers and corresponding log files in order to improve the performance of the logging process. While serial logging assumes conflicts between every pair of transactions in the serializable order, parallel logging looks at the "true" dependency. While pairs of transactions with true dependency have to log seqentially, independent transactions should log in parallel. The parallel logging algorithm implements this key observation by explicitly tracking the dependency information between different transactions. In addition, the concurrency control algorithm is implemented to ensure the serializability of the transactions that we have parsed into different threads.

Recall from the serial logging algorithm section that there are four types of dependcies, of which WAW and RAW must be maintained. We argue, however, that WAR dependency, also known as **anti-dependency**, does not have to be maintained to preserve the data consistency of the system. To illustrate our claim, we may look at the following example.

Even if the system crashes before transaction 1 is logged and after transaction 2 is logged, there will be no conflicts in data consistency during recovery. All the values in the data tuples reflect the exact state of the system immediately before the crash. Transaction 1 does not have any side effect on tuple $A$ in the database system, so whether it logs or not does not affect transaction 2.

Note that this will significantly decrease the time complexity of the logging algorithm because the number of writers to a data tuple is significantly smaller than the number of readers. In other words, transaction $A$ depends on the all the transactions executed before $A$ that write to $A$'s data tuples; therefore, $A$ can be logged once all the last writers to its data tuples have been logged.

To implement our algorithm, we specify the maximum log sequence number (LSN) in each log file that the transaction currently being logged depends on. When we attempt to log a transaction to the file, we compare the LSN that the transaction depends on ($A$) to the maximum LSN that has already been logged in each file ($B$). If $A \leq B$, the transaction is ready for logging; if $A > B$, we will push the transaction into a waiting queue after arbitrarily assigning it a LSN. The waiting queue will be checked periodically later on to see if any of its contents becomes ready for logging.

We use the following example to demonstrate the mechanism of our parallel logging algorithm:

Figure 5: Example for Parallel Logging Algorithm and Recovery

Serializable Order

| Txns: | Operations: |
|---|---|
| 1 | Read A;<br>Read B;<br>Write C; |
| 2 | Read A;<br>Write B; |
| 3 | Write A;<br>Write B;<br>Read C; |

Recovery

| LSN | Txn ID | Data Tuple | Dependency info |
|---|---|---|---|
| Log File 1 | | | |
| 1 | 1 | C | [0, 0] |
| 2 | 3 | A | [1,1] |
| | | B | |
| Log File 2 | | | |
| 1 | 2 | B | [0,0] |

As we mentioned earlier, if we were to use the serial logging algorithm, we would be forced to log the three transactions one by one; when handling big data systems, this can be a serious bottleneck. Meanwhile, the parallel logging algorithm allows us to log multiple transactions with low latency. In this case, note that transactions 1 and 2 can be logged independently since tuple $A$ has no dependency and tuple $B$ is WAR, which, per our discussion above, allows for independent logging. Therefore, if transactions 1 and 2 are parsed into two different threads, they can both be logged without waiting. Transaction 3 depends on transaction 1 due to tuple $C$ (RAW) and on transaction 2 due to tuple $B$ (WAW), so it will be put into the waiting queue until both transaction 1 and 2 have already been logged. We follow a similar process during recovery: we read the maximum LSN in each file that the current transaction depends on, and we compare it with the maximum LSN that has been recovered from that file. This ensures the serializability of the log records while improving the efficiency of the recovery process. In this particular example, two different threads take care of the two log files. While transactions 1 and 2 can be recovered immediately, transaction 3 is pushed into

the waiting queue until both 1 and 2 have already been recovered.

A visualization of the comparison of three log algorithm is below.

# 5 Evaluation

The original goal of the project is to create a scalable logging algorithm that does not act as a bottleneck for the database as a whole. The data shown below was collected to determine the scalability of the algorithm.

The results in figure 6 are used to show the scalability of the serial logging algorithm with and without the opitimization described earlier. The graph indicates the amount of time one txn would take to log. The goals are to minimize the amount the time increases as the thread count increases, indicating high scalability and decreasing the average log time per transaction. Each experiment was tested on a maximum of 10000 txns and buffer sizes ranging from 10 to 100. 10 tests were run for each buffer size, and the average of these 10 test are shown below.

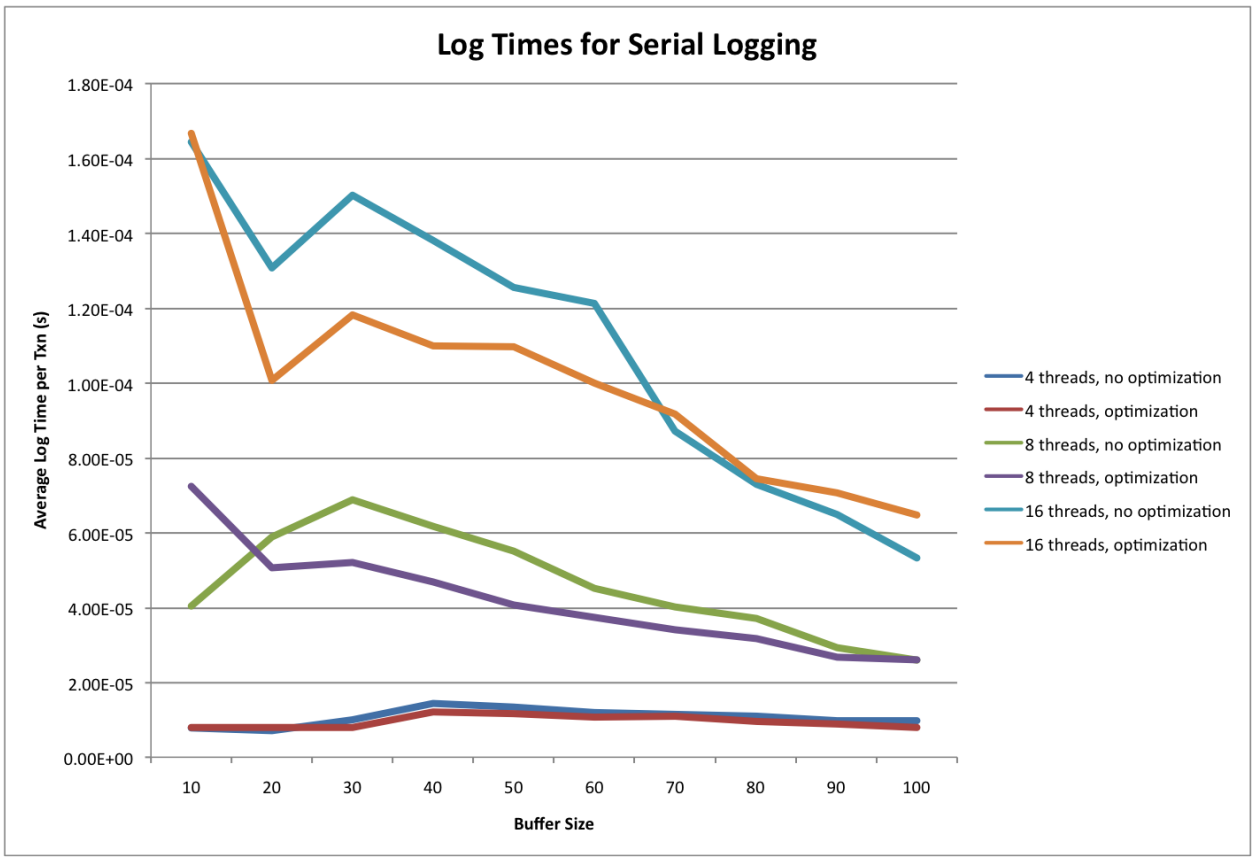
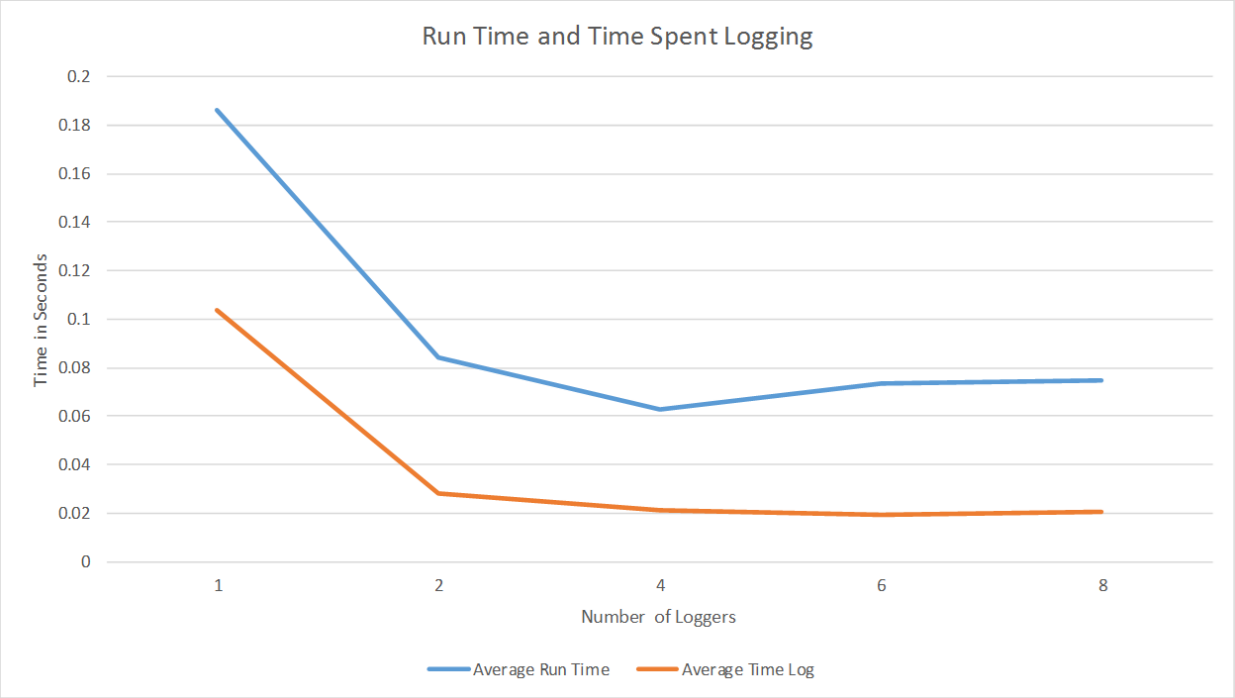



Figure 6: Serial logging results

The results from figure 6 do not portray the deseired scalability. As thread size increases, the average log time per txn increases dramatically as well. As the thread count increases, however, the buffer size becomes more important, and a larger buffer size yields a lower

Figure 7: Batch Logging Results




average log time per transaction, which is desired. This trend is oberserved because a larger buffer size man that more data is being put on the buffer, limiting the number of times buffers must flush to the disk. The disk is slow, so the number of times the disk is access should be minimzied. As thread count increases, the number of times buffers must be flushed also increases, meaning that a larger buffer size becomes more important with an increase in thread count.

After testing the scalability of serial logging, batch logging was tested to determine its effieciency. Various implementations of batch logging were tesed with a different number of loggers. The average total run time and average time spent logging were recorded and graphed. Since we want to reduce run and logging times, lower is better. We expected an increase in the number of loggers to correspond with faster run and logging times, and the results back that hypothesis.

# 6 Conclusion

After implementing serial logging and batch logging and gathering results for these algorithms, it is clear that exisiting logging algorithms have worked on smaller data sets in the past but are becoming out of date. As data sets grow, these algorithms are not efficient or scalable enough to keep up with the growth of data. Although more optimization are still being implemented for these two algorithms, the results are expected to be the same.

This makes the demand for new logging algorithm, parallel logging, even greater. Results are still being gathered, but it is predicted that this new process will be more effiecient and scalable. The key insights explain in this paper have lead to the discovery of parallel logging,

a new alorithm that can change the efficieny of current database logging.