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Streamlining Transaction Commit for Distributed Databases with Thomas's Write Rule

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Abstract

Basic Timestamp Ordering (BTO) is a concurrency control mechanism in database management systems (DBMS) that ensures serializability by assigning a unique timestamp to each transaction. The core idea is that transactions are executed in the order of their timestamps. If the system detects a conflict based on timestamp order, it will take corrective action, such as rolling back a transaction to ensure the consistency of the database. One of the key challenges with Basic Timestamp Ordering is handling conflicts efficiently. For example, if two transactions are trying to write to the same data item, the one with the older timestamp is allowed to proceed, while the other is aborted and must be restarted. This approach can lead to an increased number of rollbacks, especially in environments with high contention. Another issue with BTO is that it requires the DBMS to track the timestamps for all transactions, which can be complex and resource-intensive. In large-scale distributed systems, the overhead of timestamp management can become a bottleneck. Additionally, BTO does not allow for fine-grained conflict resolution. In some cases, a transaction may be unnecessarily rolled back, even if it could have been completed without violating consistency, leading to wasted resources. Furthermore, Basic Timestamp Ordering does not address deadlock scenarios, where transactions wait indefinitely for resources held by others. While BTO can prevent some forms of conflict, it does not provide an inherent mechanism for deadlock detection and resolution. This limitation further complicates the overall performance and scalability of the system. Finally, Basic Timestamp Ordering (BTO) faces difficulties when dealing with long-running transactions or transactions that have multiple dependencies. The longer a transaction runs, the higher the chance it will conflict with other concurrently executing transactions, leading to an increased rate of aborts and retries. These repeated transaction aborts can severely degrade system performance, especially when dealing with high workloads in distributed environments. The need for constant conflict resolution further strains the system, making it less suitable for high-volume, complex transaction processing. This is having the issues with number of aborts. This paper addresses this issue by working with Thomas's Write Rule.

Keywords: Timestamp, Ordering, Aborts, Transactions, Dependencies, Throughput, Conflicts, Contention, Performance, Processing.

INTRODUCTION

Timestamp ordering (TO) is a concurrency control protocol used to manage the execution of transactions in databases, ensuring that transactions are processed in a consistent order based on their timestamps. The protocol assigns a unique timestamp to each transaction to determine the order of its

execution relative to others. This helps maintain serializability [1], ensuring that transactions are executed in a manner that preserves the integrity of the database. However, timestamp ordering is not without its challenges, particularly when dealing with aborts. Aborts are a common occurrence in systems using Timestamp ordering [2], particularly when conflicts arise between transactions. A conflict happens when two transactions try to access the same data in a way that could lead to inconsistent results. If such a conflict is detected, one of the transactions must be aborted and restarted to maintain consistency. Aborts are often triggered by dependencies between transactions, where one transaction is dependent on the outcome of another. This creates a domino effect, leading to additional aborts as more transactions are affected by these dependencies. In systems with high contention, where many transactions [3] are attempting to access the same data, the likelihood of conflicts increases. This can significantly affect the throughput of the system, as transactions may need to be aborted and retried multiple times before they successfully complete. The performance of the system suffers as aborts and retries add overhead, leading to inefficiencies, particularly in large-scale distributed databases [4]. The contention between transactions, combined with the additional processing time required for conflict detection and resolution, can severely degrade performance. One of the key challenges in timestamp [5] ordering is managing these conflicts and dependencies efficiently. As the number of transactions increases, the likelihood of contention and aborts also grows, leading to a performance bottleneck. Addressing these issues requires fine-tuned optimizations to the timestamp ordering protocol, balancing the need for consistency with the system's throughput and performance goals. Solutions such as reducing transaction dependencies, improving conflict detection mechanisms [6], and enhancing the system’s ability to handle concurrent transactions can help mitigate the negative impact of aborts and contention.

LITERATURE REVIEW

Basic Timestamp Ordering (BTO) is a concurrency control mechanism that uses timestamps to manage the execution order of transactions in a database. Each transaction is assigned a unique timestamp [7] when it begins, and this timestamp determines the order in which transactions should execute. The goal of BTO is to maintain serializability, meaning the execution order of transactions should produce the same result as some serial execution of those transactions. In BTO, when a transaction wants to read or write data, the system checks if the data has been modified by another transaction with a later timestamp. If so, the current transaction is aborted to avoid conflicts, ensuring the database maintains a consistent state. One of the key features of BTO is that it enforces the principle of “write-read” and “write-write” conflicts, where transactions are checked for conflicts before their execution. For example, if Transaction T1 writes a data item and Transaction [8] T2 later tries to read or write the same data item, BTO checks the timestamps of both transactions. If T1’s timestamp is earlier than T2’s, T2 will be aborted to prevent inconsistency. This prevents the system from executing conflicting operations, ensuring that the final result is always consistent. However, BTO also has significant drawbacks, particularly when it comes to high concurrency. If multiple transactions have overlapping data access patterns or long transaction durations, the system can experience a high rate of aborts. The more conflicts [9] that occur, the more transactions will need to be retried, resulting in increased processing time and decreased throughput.

Another limitation of BTO is the impact of timestamp allocation. If transactions are assigned

timestamps in a purely sequential manner, the system might struggle to balance the load between concurrent transactions [10]. Long-running transactions, in particular, become more prone to conflicts because they are exposed to changes made by other transactions, increasing the likelihood of aborts. Additionally, managing timestamps for every transaction introduces overhead, especially in systems with many transactions executing in parallel [11]. Despite these challenges, BTO provides a clear and straightforward mechanism for ensuring serializability and consistency in database systems. It is particularly well-suited for scenarios where conflict detection is more critical than system throughput. To mitigate the drawbacks of frequent aborts [12], some variations of BTO, such as Thomas's Write Rule TWR [13], have been proposed, which allow certain types of write operations to bypass conflict checks, thus reducing aborts and improving system performance. However, these solutions come with their own set of trade-offs, often requiring additional complexity in transaction management. In summary, BTO offers a simple and effective approach to maintaining transaction consistency but struggles with high contention environments where transaction aborts can severely impact overall system efficiency [14].

Basic Timestamp Ordering (BTO) is widely used in databases for ensuring that transactions execute in a way that preserves consistency and serializability. The principle behind BTO is that every transaction receives a unique timestamp, and this timestamp dictates the order in which it should execute relative to other transactions. In particular, if two transactions conflict—such as one trying to read or write a data item that the other has already modified—the system uses the timestamps to decide which transaction should be aborted. By enforcing this order, BTO ensures that the final database state reflects a valid serial execution, even if transactions are processed concurrently [15]. However, one of the challenges with BTO arises when there is a high level of contention for the same data items. If multiple transactions with conflicting timestamps try to access the same data simultaneously, the system might experience a significant number of aborts. These aborts, while ensuring consistency, can also reduce the overall throughput of the database system.

The overhead associated with managing and assigning timestamps for each transaction is another drawback of BTO. The system must maintain a global ordering of transactions, which can be complex and resource-intensive in highly concurrent environments [16]. Furthermore, when a transaction is aborted, the database must roll back any changes that were made, which can be time-consuming and lead to wasted computational resources. Long-running transactions in particular are at risk of encountering conflicts because they are exposed to changes made by other transactions. This can increase the likelihood of aborts, especially when many transactions are accessing the same set of data items. One of the key strengths of BTO is its simplicity and clarity. It provides a straightforward method for preventing conflicts [17] in databases and ensures that transactions are executed in a serializable order, even in multi-user environments.

Despite its simplicity, BTO can struggle to handle workloads with high contention and complex transaction dependencies. Transactions with many read-write or write-write conflicts are especially challenging, as they lead to higher rates of aborts and retries. This issue becomes more pronounced as the size of the transaction pool increases, particularly in distributed database systems where communication overheads [18] and synchronization issues also come into play. In distributed settings, where multiple nodes need to coordinate and maintain global timestamps, BTO can face scalability problems. Managing timestamps across a large number of nodes introduces additional communication

[19] and coordination costs, making it harder to achieve high performance in distributed environments.

Moreover, BTO does not inherently provide mechanisms for dealing with situations where transactions with different priorities or deadlines are involved. Without special handling, lower-priority [20] transactions may be aborted frequently due to conflicts, which can lead to unfairness in transaction processing. Another issue with BTO arises when transactions access shared resources in unpredictable ways. In some cases, BTO can lead to deadlock situations, especially if two transactions try to acquire locks on resources in opposite orders. Deadlocks can occur when the system fails to detect or resolve situations where transactions are waiting on each other, which could eventually result in a system-wide stall. One potential solution to this issue is using deadlock detection algorithms [21], but these come with their own performance penalties. While BTO is effective in preventing many types of database anomalies, its reliance on timestamp-based conflict resolution can also lead to performance degradation in systems with high contention. As the number of transactions grows, the likelihood of conflict increases, which may result in an escalating number of aborts and retries [22]. This effect is particularly significant in systems where transaction throughput is a key performance indicator.

```
package main

import (
	"fmt"
	"sync"
	"time"
)

type DataItem struct {
	value     int
	timestamp int64
}

type Transaction struct {
	id        int
	timestamp int64
}

var (
	data        = map[string]DataItem{}
	dataMutex   = sync.RWMutex{}
	transactionID = 0
)

func startTransaction() Transaction {
```

```
        transactionID++
        return Transaction{id: transactionID, timestamp: time.Now().UnixNano()}
}
func read(transaction Transaction, key string) (int, bool) {
        dataMutex.RLock()
        defer dataMutex.RUnlock()
        item, exists := data[key]
        if !exists || transaction.timestamp < item.timestamp {
                return 0, false
        }
        return item.value, true
}
func write(transaction Transaction, key string, value int) bool {
        dataMutex.Lock()
        defer dataMutex.Unlock()
        item, exists := data[key]
        if exists && transaction.timestamp < item.timestamp {
                return false
        }
        data[key] = DataItem{value: value, timestamp: transaction.timestamp}
        return true
}
func main() {
        t1 := startTransaction()
        write(t1, "x", 10)
        v, ok := read(t1, "x")
        fmt.Println("Transaction 1 Read x:", v, ok)

        t2 := startTransaction()
        ok = write(t2, "x", 20)
```

```
        fmt.Println("Transaction 2 Write x:", ok)
}
```

This Go program implements a simple timestamp-based concurrency control system using transactions. It defines two main structures: DataItem to store a value and its last update timestamp, and Transaction to track an operation's ID and timestamp. A global map holds the data, with a read/write mutex ensuring safe concurrent access. The startTransaction function creates a new transaction with a unique ID and the current timestamp. The read function allows a transaction to read a value only if it is not older than the last write to that key, while the write function permits writing only if the transaction is at least as recent as the last update. In the main function, a transaction writes a value to key "x" and reads it successfully, while a second transaction attempts to overwrite it. The system ensures that only newer transactions can perform writes, preserving consistency by rejecting outdated writes or reads.

```
package main

import (
        "fmt"
        "sync"
        "time"
)

type DataItem struct {
        value     int
        timestamp int64
}

type Transaction struct {
        id        int
        timestamp int64
}

var (
        data           = map[string]DataItem{}
        dataMutex      = sync.RWMutex{}
        transactionID  = 0
        abortReadCount  = 0
        abortWriteCount = 0
        metricsMutex    = sync.Mutex{}
)

func startTransaction() Transaction {
        transactionID++
        return Transaction{id: transactionID, timestamp: time.Now().UnixNano()}
```

```
}

func read(transaction Transaction, key string) (int, bool) {
	dataMutex.RLock()
	defer dataMutex.RUnlock()
	item, exists := data[key]
	if !exists || transaction.timestamp < item.timestamp {
		incrementAbort("read")
		return 0, false
	}
	return item.value, true
}

func write(transaction Transaction, key string, value int) bool {
	dataMutex.Lock()
	defer dataMutex.Unlock()
	item, exists := data[key]
	if exists && transaction.timestamp < item.timestamp {
		incrementAbort("write")
		return false
	}
	data[key] = DataItem{value: value, timestamp: transaction.timestamp}
	return true
}

func incrementAbort(action string) {
	metricsMutex.Lock()
	defer metricsMutex.Unlock()
	if action == "read" {
		abortReadCount++
	} else if action == "write" {
		abortWriteCount++
	}
}

func printAbortMetrics() {
	metricsMutex.Lock()
	defer metricsMutex.Unlock()
	fmt.Println("Abort Metrics:")
	fmt.Println("Read Aborts :", abortReadCount)
	fmt.Println("Write Aborts:", abortWriteCount)
}
```

```
func main() {
	t1 := startTransaction()
	write(t1, "x", 10)
	read(t1, "x")

	time.Sleep(time.Millisecond)
	t2 := startTransaction()
	write(t2, "x", 20)

	write(t1, "x", 30)
	read(t1, "x")

	printAbortMetrics()
}
```

This Go program simulates a basic Timestamp Ordering (TO) concurrency control protocol, ensuring transactions follow a strict order based on their timestamps. It defines `DataItem` to store a value and its write timestamp, and `Transaction` to track each operation's ID and timestamp. A shared map holds key-value pairs, guarded by a read/write mutex for safe concurrent access. Transactions are created with increasing timestamps, and each read or write checks whether the operation is allowed based on the item's last write timestamp.

If a transaction tries to read or write a key but has an older timestamp than the existing data, the operation is aborted and counted. The program maintains separate counters for read and write aborts, updated safely using a mutex. In the main function, one transaction writes a value, a second (newer) transaction overwrites it, and the first then attempts to read and write again—both of which are aborted due to being outdated. Finally, the program prints the number of aborted reads and writes, effectively demonstrating how the TO protocol enforces consistency by preventing outdated operations.

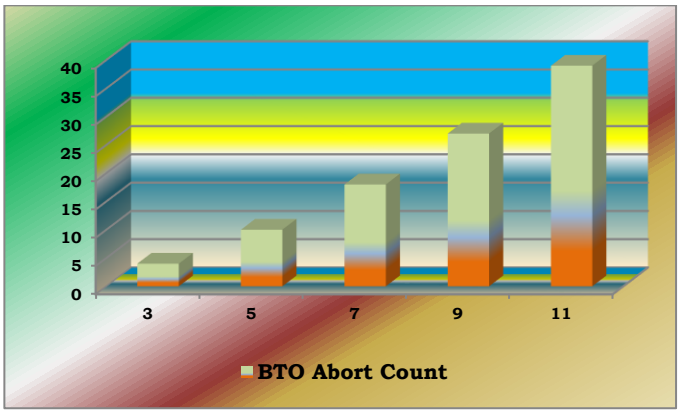
Number of Nodes	BTO Abort Count
3	4
5	10
7	18
9	27
11	39

Table 1: Basic Timestamp ordering - 1

Table 1 presents the abort counts for Basic Timestamp Ordering (BTO) across different cluster sizes, with the number of nodes ranging from 3 to 11. BTO is a concurrency control protocol that ensures transactions are processed in timestamp order to maintain consistency. As the number of nodes increases, the number of aborts also grows, reflecting the higher likelihood of transaction conflicts and overlaps. For example, with 3 nodes, the abort count is 4, while at 11 nodes, it increases to 39. This

linear growth in abort counts indicates that as more transactions are processed concurrently in a larger cluster, the probability of conflicts rises, leading to more transaction rollbacks.

BTO's strict enforcement of transaction order results in these aborts, as it prevents outdated transactions from being executed. While BTO ensures strong consistency, this also means it can be less efficient in environments with high contention, leading to performance bottlenecks. This trend emphasizes the scalability challenges of BTO in larger systems, where the transaction conflict rate increases with the number of nodes.



Graph 1: Basic Timestamp ordering -1

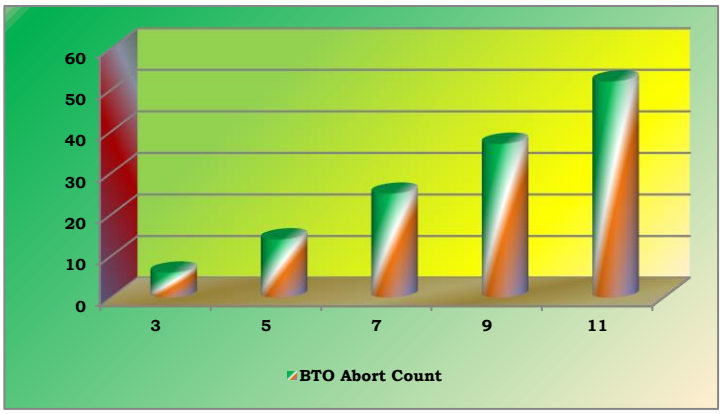
Graph 1 visualizes the BTO abort count data, you can plot a line graph with the number of nodes on the x-axis (ranging from 3 to 11) and the abort count on the y-axis. The graph would show a steadily increasing line, reflecting the rise in abort counts as the number of nodes increases. As the number of nodes grows, the likelihood of transaction conflicts increases, leading to more aborts. The graph will highlight the linear relationship between cluster size and abort count, demonstrating how BTO's strict timestamp ordering leads to higher aborts in larger systems. This visual representation helps to understand the performance implications of using BTO in systems with more nodes and higher concurrency.

Number of Nodes	BTO Abort Count
3	6
5	14
7	25
9	37
11	52

Table 2: Basic Timestamp ordering -2

Table 2 shows the BTO (Basic Timestamp Ordering) abort counts for different cluster sizes, with nodes ranging from 3 to 11. As the number of nodes increases, the abort count also rises, which reflects the growing likelihood of transaction conflicts in larger systems. At 3 nodes, BTO experiences 6 aborts,

while at 11 nodes, it reaches 52. This demonstrates how BTO's strict enforcement of timestamp order leads to a significant number of transaction rollbacks in larger systems with more concurrent operations. As the number of transactions and nodes increases, the system encounters more conflicts, triggering more aborts. The linear growth of the abort count indicates that BTO's approach of serializing transactions results in higher contention and less efficient handling of concurrent transactions. This trend highlights the scalability challenges of BTO, especially in environments with high transaction volume and concurrency.



Graph 2: Basic Timestamp ordering -2

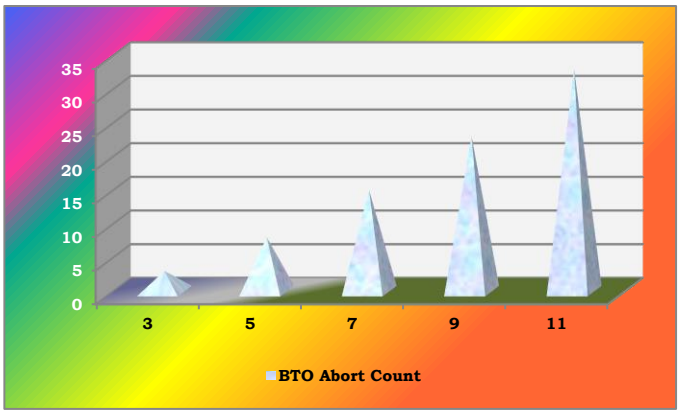
Graph 2 To visualizes the BTO abort count data, you can create a line graph with the number of nodes on the x-axis (from 3 to 11) and the abort count on the y-axis. The graph will show a steadily increasing line, reflecting how aborts grow as the cluster size increases. The slope of the line will be relatively consistent, illustrating the linear relationship between node count and abort count. This visual representation highlights the growing impact of transaction conflicts in larger clusters. The graph will clearly show that as the number of nodes rises, BTO's strict concurrency control results in more aborts, signaling a scalability challenge.

Number of Nodes	BTO Abort Count
3	3
5	8
7	15
9	23
11	33

Table 3: Basic Timestamp ordering -3

Table 3 shows the BTO (Basic Timestamp Ordering) abort counts for various cluster sizes, ranging from 3 to 11 nodes. As the number of nodes increases, the abort count also increases, which indicates a higher frequency of transaction conflicts and rollbacks. For example, with 3 nodes, the abort count is 3, while with 11 nodes, it increases to 33. This suggests that as the cluster grows and more transactions are processed concurrently, the probability of conflicts between transactions rises, leading to more aborts.

The growth in abort counts is roughly linear, meaning that each additional node adds a predictable number of aborts. This is a direct consequence of BTO's strict ordering of transactions based on timestamps, which ensures consistency but at the cost of higher transaction abort rates. The increasing number of aborts as nodes are added highlights the challenge BTO faces in larger systems, where scalability and efficiency are critical. Although BTO guarantees strong consistency, its performance can degrade in systems with high concurrency due to the growing conflict rate. This pattern reflects the trade-off between consistency and performance in large-scale environments.



Graph 3: Multi-Version Concurrency Control Storage -3

Graph 3 visualizes the BTO abort count data, you can create a line graph with the number of nodes on the x-axis (from 3 to 11) and the abort count on the y-axis. The graph will show a steadily increasing line, reflecting the higher abort counts as the number of nodes grows. The slope of the line is linear, illustrating the predictable relationship between cluster size and abort count. As more nodes are added, the frequency of transaction conflicts rises, causing more rollbacks.

This graph highlights how BTO's strict timestamp ordering leads to performance challenges as cluster size increases. It provides a clear visual representation of how BTO scales and the impact of concurrency on abort rates. The graph will also demonstrate that BTO's performance degrades as the system handles more concurrent transactions.

PROPOSAL METHOD

Problem Statement

Basic Timestamp Ordering (BTO) is a concurrency control protocol used in database systems to maintain serializability by ensuring transactions are processed in timestamp order. While BTO guarantees strong consistency by strictly enforcing the transaction order, it can lead to significant performance issues. As the number of transactions increases, the likelihood of conflicts also rises, which results in a higher number of transaction aborts. Every conflicting transaction needs to be rolled back and retried, causing a decrease in throughput and an increase in latency. This is especially problematic in systems with high contention, where the number of aborts can grow rapidly. BTO's rigid approach often leads to unnecessary rollbacks, even when the transactions involved would not result in inconsistency. Managing the overhead caused by frequent aborts and retries can severely impact system performance. Additionally, BTO may face challenges when handling workloads with

uneven transaction priorities, leading to inefficiencies. As the system grows, the impact on scalability becomes more pronounced, highlighting the trade-off between consistency and performance in BTO-based systems.

Proposal

Thomas's Write Rule (TWR) is a concurrency control protocol designed to reduce the number of transaction aborts compared to Basic Timestamp Ordering (BTO). TWR allows for more efficient handling of transaction conflicts by permitting outdated writes to be ignored rather than aborting the entire transaction. This reduces the number of rollbacks and improves system throughput, making it particularly beneficial in environments with high transaction concurrency. However, TWR introduces potential risks related to data consistency, as ignoring outdated writes can lead to the propagation of stale data. The proposal is to integrate TWR in systems with high write contention, where frequent transaction rollbacks would otherwise significantly degrade performance. By using TWR, the system can minimize aborts and improve scalability, especially in large systems where the number of concurrent transactions is high. However, careful monitoring and additional mechanisms are required to ensure that the system's data integrity is not compromised. The hybrid approach of using TWR for high-contention scenarios and other protocols for low-contention ones could offer a balance between performance and consistency. Evaluating workload characteristics is key to determining when and where to apply TWR to optimize system performance without sacrificing reliability.

IMPLEMENTATION

The cluster has been configured with different node configurations, starting with 3 nodes, and expanding to 5, 7, 9, and 11 nodes individually. Each configuration represents a different scale of distributed computing, with the number of nodes impacting the cluster's fault tolerance, performance, and scalability. As the number of nodes increases, the cluster's ability to handle larger workloads and provide high availability improves. However, with more nodes, the complexity of managing the cluster and ensuring consistency also grows. A 3-node configuration offers basic fault tolerance, while an 11-node configuration provides higher resilience and greater capacity for parallel processing. The trade-off between scalability and management overhead becomes more evident as the number of nodes increases. Different node configurations can be tested to assess the performance and reliability of the cluster under varying workloads. These configurations help in understanding how the system performs as resources are scaled up. Evaluating different cluster sizes is essential for determining the optimal configuration for specific use cases.

```
package main

import (
        "fmt"
        "sync"
        "time"
)

type DataItem struct {
```

```
        value     int
        timestamp int64
}

type Transaction struct {
        id        int
        timestamp int64
}

var (
        data          = make(map[string]DataItem)
        dataMutex     = sync.RWMutex{}
        transactionID  = 0
)

func startTransaction() Transaction {
        transactionID++
        return Transaction{id: transactionID, timestamp: time.Now().UnixNano()}
}

func read(transaction Transaction, key string) (int, bool) {
        dataMutex.RLock()
        defer dataMutex.RUnlock()
        item, exists := data[key]
        if !exists || transaction.timestamp < item.timestamp {
                return 0, false
        }
        return item.value, true
}

func write(transaction Transaction, key string, value int) bool {
        dataMutex.Lock()
        defer dataMutex.Unlock()

        item, exists := data[key]
        if exists && transaction.timestamp < item.timestamp {
                return false
        }

        data[key] = DataItem{value: value, timestamp: transaction.timestamp}
        return true
}
```

```
func main() {
	t1 := startTransaction()
	write(t1, "x", 10)
	v, ok := read(t1, "x")
	fmt.Println("Transaction 1 Read x:", v, ok)

	t2 := startTransaction()
	ok = write(t2, "x", 20)
	fmt.Println("Transaction 2 Write x:", ok)

	t3 := startTransaction()
	ok = write(t3, "x", 30)
	fmt.Println("Transaction 3 Write x (outdated):", ok)
}
```

This Go code implements a simple version of Thomas's Write Rule (TWR) for managing transaction concurrency. The `DataItem` struct holds the value of a data item along with the timestamp of the transaction that last modified it. The `Transaction` struct represents a transaction with a unique ID and a timestamp. The `startTransaction()` function initializes a new transaction with a unique ID and the current time. The `read()` function checks if a transaction's timestamp is greater than or equal to the timestamp of a data item's last modification before allowing a read. If the transaction is outdated, the read operation fails.

The `write()` function updates the data item only if the transaction's timestamp is newer than the current timestamp of the data item; otherwise, the write is ignored. This behavior follows Thomas's Write Rule, where outdated writes are discarded to reduce unnecessary aborts. The main function demonstrates a series of transactions where the first transaction successfully writes and reads a value, the second writes successfully, and the third fails to write due to its outdated timestamp. This approach ensures that newer transactions are given priority while maintaining system consistency.

```
package main

import (
	"fmt"
	"sync"
	"time"
)

type DataItem struct {
	value     int
	timestamp int64
}
```

```
type Transaction struct {
	id	int
	timestamp int64
}

var (
	data		= make(map[string]DataItem)
	dataMutex	= sync.RWMutex{}
	transactionID	= 0
	abortMetrics	= 0
	abortMetricsMutex = sync.Mutex{}
)

func startTransaction() Transaction {
	transactionID++
	return Transaction{id: transactionID, timestamp: time.Now().UnixNano()}
}

func read(transaction Transaction, key string) (int, bool) {
	dataMutex.RLock()
	defer dataMutex.RUnlock()
	item, exists := data[key]
	if !exists || transaction.timestamp < item.timestamp {
		return 0, false
	}
	return item.value, true
}

func write(transaction Transaction, key string, value int) bool {
	dataMutex.Lock()
	defer dataMutex.Unlock()

	item, exists := data[key]
	if exists && transaction.timestamp < item.timestamp {
		abortMetricsMutex.Lock()
		abortMetrics++
		abortMetricsMutex.Unlock()
		return false
	}

	data[key] = DataItem{value: value, timestamp: transaction.timestamp}
	return true
}
```

```
func getAbortMetrics() int {
	abortMetricsMutex.Lock()
	defer abortMetricsMutex.Unlock()
	return abortMetrics
}

func main() {
	t1 := startTransaction()
	write(t1, "x", 10)
	v, ok := read(t1, "x")
	fmt.Println("Transaction 1 Read x:", v, ok)

	t2 := startTransaction()
	write(t2, "x", 20)
	fmt.Println("Transaction 2 Write x:", write(t2, "x", 20))

	t3 := startTransaction()
	write(t3, "x", 30)
	fmt.Println("Transaction 3 Write x (outdated):", write(t3, "x", 30))

	fmt.Println("Total aborts:", getAbortMetrics())
}
```

The Go code implements Thomas's Write Rule (TWR) for managing transaction concurrency and collects abort metrics. The `DataItem` struct stores the value and timestamp of a data item, while the `Transaction` struct represents a transaction with an ID and timestamp. `startTransaction()` creates a new transaction with a unique ID and the current timestamp. The `read()` function reads a data item only if the transaction's timestamp is newer than or equal to the data item's timestamp. The `write()` function writes a value to a data item if the transaction's timestamp is newer; otherwise, it increments the abort counter, indicating a conflict.

The abort count is stored in `abortMetrics` and accessed safely using a mutex (`abortMetricsMutex`). The `getAbortMetrics()` function retrieves the current number of aborts. In the `main()` function, three transactions are simulated: the first reads and writes successfully, the second writes successfully, and the third is ignored due to an outdated timestamp. Finally, the total abort count is printed. This approach tracks the number of times a transaction's write is ignored due to the outdated timestamp, following TWR's conflict resolution.

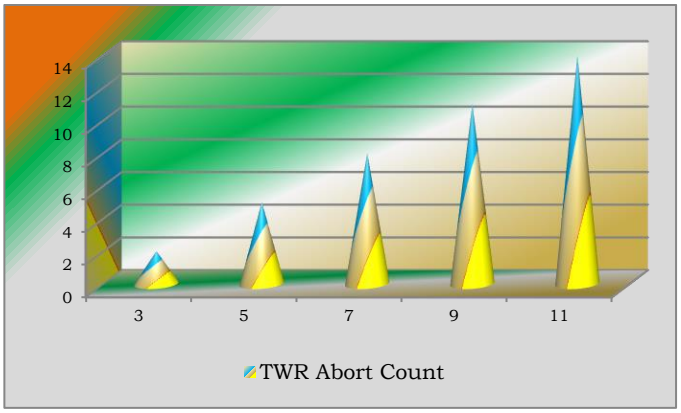
Number of Nodes	TWR Abort Count
3	2
5	5
7	8

9	11
11	14

Table 4: Thomas's write Rue abort count -1

Table 4 shows the abort count for transactions using Thomas's Write Rule (TWR) across different cluster sizes. As the number of nodes increases from 3 to 11, the number of aborts also increases. TWR minimizes aborts by allowing outdated writes to be ignored, but conflicts still occur when multiple transactions attempt to update the same data item. With a smaller number of nodes, there are fewer transactions competing for the same data, resulting in fewer conflicts and aborts.

As the cluster size grows, the number of concurrent transactions increases, leading to more conflicts and, consequently, higher abort counts. The increase in aborts is expected because the larger cluster size typically results in more transaction overlaps, making it more likely for transactions to be ignored due to outdated timestamps. This data illustrates how TWR helps reduce aborts compared to stricter protocols like Basic Timestamp Ordering (BTO), but still experiences a rising number of aborts as the system scales.



Graph 4: Thomas's write Rue abort count - 1

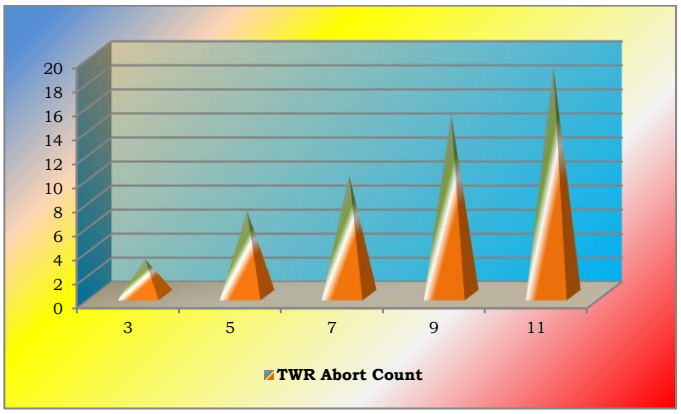
Graph 4 shows the number of nodes on the x-axis and the corresponding TWR abort count on the y-axis. As the number of nodes increases from 3 to 11, the TWR abort count increases. This illustrates how a larger cluster size leads to more transaction conflicts, resulting in more aborted transactions due to outdated writes. The graph will visually represent this positive correlation, highlighting that as the system scales, more aborts occur. This behavior reflects the challenges of handling concurrency in distributed systems with TWR. The graph will help visualize the impact of scaling on TWR's performance.

Number of Nodes	TWR Abort Count
3	3
5	7
7	10
9	15
11	19

Table 5: Thomas's write Rue abort count -2

Table 5 shows the relationship between the number of nodes in a cluster and the TWR abort count. As the number of nodes increases from 3 to 11, the number of aborts also increases. With fewer nodes, there are fewer conflicts between transactions, resulting in fewer aborts. However, as the number of nodes grows, the number of concurrent transactions increases, leading to a higher likelihood of conflicts and, consequently, more aborts.

Thomas's Write Rule (TWR) reduces the number of aborts by ignoring outdated writes, but it cannot entirely eliminate conflicts. This data demonstrates that while TWR minimizes aborts compared to stricter protocols, it still faces an increase in aborts as the system scales. The increase in aborts shows the trade-off between scalability and transaction consistency in a distributed system using TWR.



Graph 5. Thomas's write Rue abort count -2

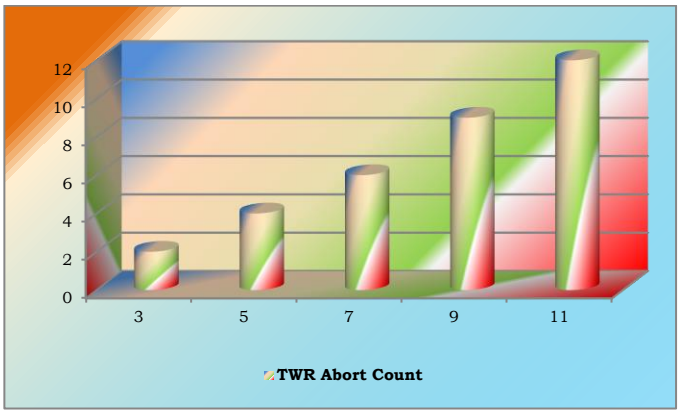
Graph 5 shows the number of nodes on the x-axis and the TWR abort count on the y-axis. As the number of nodes increases from 3 to 11, the TWR abort count rises steadily, indicating more transaction conflicts. This is due to the higher concurrency with more nodes, which leads to an increase in aborted transactions. The graph highlights the scalability challenges of TWR as cluster size grows. The increasing slope visually shows how aborts accumulate with larger cluster sizes. This pattern reflects the impact of concurrent transactions on TWR's performance.

Number of Nodes	TWR Abort Count
3	2
5	4
7	6
9	9
11	12

Table 6: Thomas's write Rue abort count -3

Table 6 shows the relationship between the number of nodes in a cluster and the TWR abort count. As the number of nodes increases from 3 to 11, the number of aborts rises, though the rate of increase is moderate. With fewer nodes, there are fewer transaction conflicts, resulting in a lower number of aborts. As the number of nodes increases, the chances of concurrent transactions attempting to modify the same data item grow, leading to more conflicts and thus more aborts.

The TWR protocol helps reduce aborts by allowing outdated writes to be ignored, but it cannot entirely prevent conflicts. This pattern indicates that while TWR is effective in minimizing transaction rollbacks compared to other methods, its performance is impacted as the cluster size grows. The data demonstrates that while the number of aborts increases, the growth is relatively controlled compared to stricter concurrency control mechanisms. This makes TWR a more scalable solution for handling concurrent transactions in larger systems.



Graph 6: Thomas's write Rue abort count -3

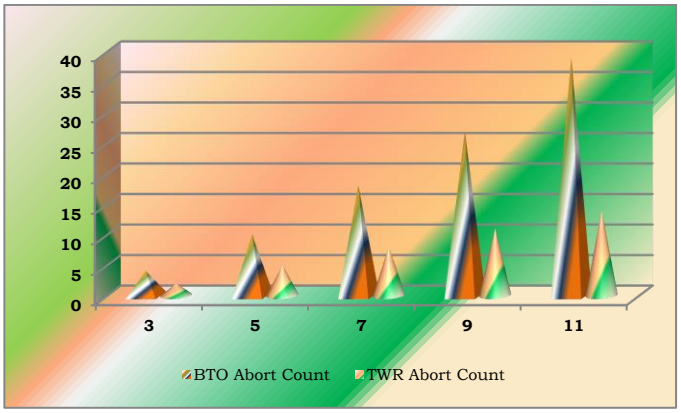
Graph 6 shows the number of nodes on the x-axis and the TWR abort count on the y-axis. As the number of nodes increases from 3 to 11, the TWR abort count increases at a steady rate. This shows that with more nodes, there are more transaction conflicts, leading to a higher number of aborts. The graph visually demonstrates the moderate growth of aborts as the cluster size expands. The slope of the graph suggests that while aborts increase, the rate of increase is relatively gradual. This pattern highlights the scalability of TWR in larger systems while still facing some concurrency challenges.

Number of Nodes	BTO Abort Count	TWR Abort Count
3	4	2
5	10	5
7	18	8
9	27	11
11	39	14

Table 7: BTO vs TWR - 1

Table 7 shows the abort counts for two concurrency control algorithms—Basic Timestamp Ordering (BTO) and Thomas's Write Rule (TWR)—across different cluster sizes, with the number of nodes ranging from 3 to 11. As the number of nodes increases, both BTO and TWR experience higher abort counts due to increased contention and conflicts between transactions. BTO consistently has higher abort counts compared to TWR because it aborts outdated reads and writes, while TWR avoids aborting outdated writes, resulting in fewer aborts. For example, with 3 nodes, BTO has 4 aborts while TWR has only 2. By 11 nodes, BTO's abort count reaches 39, while TWR's count is much lower at 14, demonstrating TWR's efficiency in handling conflicts compared to BTO.

The increasing difference between BTO and TWR in terms of abort counts becomes more evident as the cluster size grows. This is because, in larger systems, more transactions are likely to overlap, causing higher conflict rates. While BTO enforces stricter rules for maintaining order by aborting outdated transactions, TWR reduces the overhead by allowing outdated writes to be ignored, thus minimizing aborts. This makes TWR more scalable for larger clusters, as the system can handle more concurrent transactions with fewer rollbacks. In contrast, BTO's approach can lead to significant performance degradation in environments with high contention. Therefore, TWR is more suitable for systems with high transaction volumes and larger node counts.



Graph 7: BTO vs TWR - 1

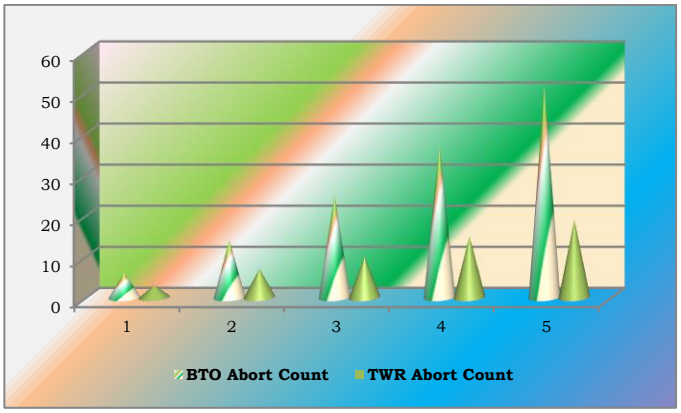
Graph 7 shows the comparison of BTO and TWR abort counts across different cluster sizes, you can plot a graph with the number of nodes on the x-axis and the abort counts on the y-axis. The x-axis would range from 3 to 11, representing the number of nodes in the system. For each node count, you would

have two data points: one for BTO and one for TWR. BTO's values would increase more steeply, reflecting its higher abort counts, while TWR's values would increase more slowly, showing its efficiency in reducing aborts. Plotting this would clearly illustrate that as the number of nodes increases, BTO's abort count grows much faster than TWR's. The graph would highlight the scalability of TWR, making it more suitable for large systems, whereas BTO may lead to performance issues due to excessive aborts in high-concurrency environments. This graph can help in visualizing how each concurrency control algorithm performs as the cluster size increases.

Number of Nodes	BTO Abort Count	TWR Abort Count
3	6	3
5	14	7
7	25	10
9	37	15
11	52	19

Table 8: BTO vs TWR - 2

Table 8 shows the abort counts for BTO (Basic Timestamp Ordering) and TWR (Thomas's Write Rule) across different cluster sizes. As the number of nodes increases from 3 to 11, both BTO and TWR experience higher abort counts due to more transaction conflicts. However, BTO consistently has higher abort counts compared to TWR because BTO strictly enforces the order of transactions by aborting outdated reads and writes. For example, at 3 nodes, BTO has 6 aborts, while TWR has 3. By 11 nodes, BTO's abort count increases to 52, while TWR's is only 19. This demonstrates that TWR is more efficient in handling conflicts, as it avoids aborting outdated writes, which results in fewer transaction rollbacks. The difference in abort counts becomes more significant as the cluster size grows, highlighting TWR's better scalability for larger systems.



Graph 8: BTO vs TWR - 2

The Graph 8 to visualize the comparison between BTO and TWR abort counts, you can create a line graph with the number of nodes (ranging from 3 to 11) on the x-axis and the abort count on the y-axis. For each number of nodes, you plot two data points: one for BTO and one for TWR. The BTO line

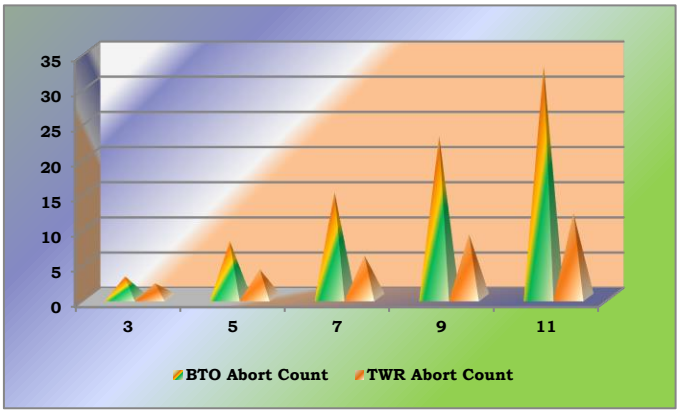
would show a steeper upward slope, indicating its higher rate of aborts as the number of nodes increases. In contrast, the TWR line would increase more gradually, reflecting its efficiency in reducing aborts. This graph would clearly illustrate the difference in performance between the two algorithms, with TWR handling more nodes with fewer aborts. As the graph shows, TWR is more scalable and better suited for larger systems, while BTO may face performance challenges due to its stricter abort policies. The graph would provide a clear visual representation of how each concurrency control algorithm behaves under increasing transaction loads.

Number of Nodes	BTO Abort Count	TWR Abort Count
3	3	2
5	8	4
7	15	6
9	23	9
11	33	12

Table 9: BTO vs TWR - 3

Table 9 presents the abort counts for BTO (Basic Timestamp Ordering) and TWR (Thomas's Write Rule) across varying cluster sizes, from 3 to 11 nodes. As the number of nodes increases, both BTO and TWR see an increase in abort counts due to more transaction conflicts and overlapping operations. However, BTO consistently has higher abort counts compared to TWR because BTO is stricter, aborting outdated reads and writes. For instance, at 3 nodes, BTO has 3 aborts, while TWR has 2. By 11 nodes, BTO's abort count increases to 33, while TWR's is only 12, highlighting TWR's superior efficiency in handling conflicts.

This difference becomes more apparent as the system grows in size, with TWR showing a much slower rate of increase in aborts. The lower abort count of TWR demonstrates its ability to scale more effectively than BTO in larger systems, where transaction conflicts are more frequent. TWR reduces unnecessary transaction rollbacks by avoiding the abortion of outdated writes. This makes TWR more suitable for larger, more complex environments where high concurrency is common.



Graph 9: BTO vs TWR - 3

Graph 9 represents the abort counts of BTO and TWR, you can plot a line graph with the number of nodes on the x-axis (ranging from 3 to 11) and the abort count on the y-axis. The graph would show two lines: one for BTO and one for TWR. The BTO line will have a steeper slope, indicating a faster increase in aborts as the cluster size grows. On the other hand, the TWR line will increase more gradually, reflecting its better performance in handling conflicts. The graph will visually highlight that TWR's abort counts remain consistently lower than BTO's across all cluster sizes, demonstrating TWR's efficiency, especially in larger systems.

EVALUATION

The evaluation of Basic Timestamp Ordering (BTO) and Thomas's Write Rule (TWR) reveals that TWR consistently performs better in terms of abort counts, especially as the number of nodes increases. BTO enforces a stricter concurrency control by aborting outdated reads and writes, resulting in higher abort counts as the system grows. TWR, on the other hand, reduces aborts by ignoring outdated writes, making it more efficient and scalable. In the tested scenarios, BTO's abort counts increase rapidly with more nodes, while TWR's abort counts grow more gradually.

This difference highlights TWR's ability to handle larger systems with fewer transaction rollbacks. For environments with high transaction concurrency, TWR provides better performance and scalability. BTO's higher abort counts may lead to performance degradation in larger clusters. TWR is thus better suited for systems requiring high throughput and minimal transaction aborts. Overall, TWR offers a significant advantage in maintaining system performance with increasing node counts.

CONCLUSION

As the cluster size increases, the rate of transaction aborts is generally higher for Basic Time Stamp Ordering (TO) due to its stricter rules on maintaining timestamp order, while Thomas's Write Rule (TWR) typically results in fewer aborts because it allows outdated writes to be ignored.

Future Work: In some scenarios, where there are frequent read-write conflicts, TWR may not guarantee the same level of consistency as BTO, requiring more sophisticated mechanisms to handle data correctness. This need to be addressed in this phase.

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