GRuB: Gas-Efficient Blockchain Storage via Workload-Adaptive Data Replication

Kai Li Syracuse University
Syracuse, NY 13244
kli111@syr.edu

Yuzhe (Richard) Tang
Syracuse University
Syracuse, NY 13244
ytang100@syr.edu

Qi (Alex) Zhang
Syracuse University
Syracuse, NY 13244
qzhang71@syr.edu

Cheng Xu
Hong Kong Baptist University
Kowloon Tong, Hong Kong
chengxu@comp.hkbu.edu.hk

Jianliang Xu
Hong Kong Baptist University
Kowloon Tong, Hong Kong

Qi (Alex) Zhang
Syracuse University
Syracuse, NY 13244
qzhang71@syr.edu

ABSTRACT
Modern Blockchains support the execution of user programs, called smart contracts. As a trusted computing platform, smart contracts bring decentralization, computation integrity, open access and information transparency to average users on the Internet. However, running smart-contract programs leads to high costs, known as Gas. Such costs prevent the use of smart contracts in data-intensive application scenarios, such as high-frequency trading and transparency logging. This paper addresses the Gas-based cost effectiveness in the most consuming layer of a smart contract, namely data storage. We present GRuB, a dynamic data-replication framework that monitors the smart-contract workload and makes online replication decisions. A new online algorithm is proposed that provides constant-bounded “competitiveness” in Gas. To further save Gas, the workload monitor and decision maker are run off the Blockchain and with security against the forging of workload trace being monitored. A GRuB prototype is built, including a smart-contract component on Ethereum and an off-chain middleware on top of Google LevelDB. The cost evaluation under the YCSB workloads shows that GRuB can converge quickly to changing workloads and save Gas significantly compared with static replication schemes. Two case studies are conducted for data-intensive applications, including high-frequency trading and transparency logging, in which running GRuB leads to affordable Gas.

1. INTRODUCTION
Recent years have witnessed the advent of smart contracts, user programs supported by the latest extensible Blockchain systems including Bitcoin, Ethereum, etc. The smart contracts provide trust decentralization, open access, computation integrity, and information transparency, and they are promising building blocks of trusted applications in various domains ranging from Information Security [10][17], finance and supply-chains, etc.

Public Blockchains are commonly designed to charge a cost for every instruction executed in a smart contract, known as Gas. It is known the Gas is a necessary defense mechanism against denial-of-service (DoS) attacks. Because smart-contract execution is replicated across all Blockchain nodes, Gas incurs a much higher monetary cost per instruction than that on a single machine (e.g., in a cloud instance). Due to this reason, the high Gas cost poses a major challenge in practice to adopt smart contracts in data-intensive applications.

In particular, the most expensive instructions in Gas are related to data storage. For instance, in Ethereum’s Gas model (Table 1), transactions and storage writes, which respectively move and store data on the Blockchain, are the two most expensive operations. Because Ethereum’s Gas model has been adaptively revised by multiple iterations (e.g., EIP150, EIP1283, EIP2028 and other EIPs [5]) to defend real-world DoS attacks in the arm race, we believe Ethereum’s Gas model is mature and representative – Its “pricing” of storage operations with high Gas is fundamental for the DoS security in replicated smart-contract execution. Therefore, to reduce the Gas, instead of revising the Gas-per-instruction model, we aim at reducing the use of storage-relevant instructions in a smart contract.

Table 1: Gas cost model of various operations in Ethereum: It can be seen that operations related to data movement (transactions) and data storage are the most expensive in Gas. The hash computation over data in memory is much cheaper.

| Operation                  | Gas cost (per 32-byte words) |
|----------------------------|------------------------------|
| Transaction                | $C_{tx}(X) = 4 + 0.0005X$     |
| Storage write (insert)     | $C_{insert}(X) = 20000X$      |
| Storage write (update)     | $C_{update}(X) = 5000X$       |
| Storage read               | $C_{read}(X) = 200X$          |
| Hash computation           | $C_{hash}(X) = 30 + 6X$       |

In this paper, we describe how dynamic data replication can be used to achieve Gas-effective data storage (i.e., with small Gas per read/write operation) in data-intensive smart contracts. It is commonly observed that data-intensive applications, particularly in finance and web scenarios, exhibit data-access workloads that vary over time. For instance, in real stock markets the exchange rate varies significantly from minutes to minutes. Existing static data replication techniques, when used in these dynamic scenarios, incur high Gas due to transactions and storage operations (see the next paragraph). The key insight of this paper is that, under constant-changing workloads, dynamic data replication can avoid high transaction fees in serving data reads, and at the same time, save expensive storage operations when serving data writes.

Concretely, consider that the primary data copy is stored off the
Blockchain, on an S3 like cloud storage service. In the first baseline design (BL1), data is never replicated on the Blockchain. Serving data reads in a smart contract requires transactions to move the off-chain data onto the Blockchain. Transactions incur high Gas per word being moved (e.g., 2176 Gas per word as in Table 1). In the second baseline design (BL2), data is always replicated on the Blockchain. Feeding a smart contract with the data updates requires writing the on-chain storage, which also incurs high Gas (e.g., 5000 or 20000 Gas per word in Table 1). Ideally, a workload-adaptive replication scheme 1) would replicate data onto the Blockchain when encountering read-intensive workloads, thus saving the transactions for reading off-chain data, and 2) would revoke data replica on the Blockchain when encountering write-intensive workloads, thus saving the storage writes on the Blockchain. By this means, it eliminates the two most expensive operations in Gas. In §2.3, we will present detailed analytical and measurement studies to show that under sufficiently dynamic workloads, dynamic replication can lead to $7 \times \sim 100 \times$ Gas savings, compared to static replication schemes.

Based on the above observation, we propose GRuB, a security protocol and middleware system for Gas-aware data Replication with Blockchains. In the target system model, illustrated in Figure 1, data updates are produced continuously from an off-chain data owner (DO) and are fed into smart contracts on the Blockchain evaluating queries on the data. The program state of the smart contract is stored, by default, in a service provider (SP), which offers data storage at low costs. The data moved from the off-chain SP to on-chain contracts are authenticated jointly by a Merkle tree on the SP and the root hash on the contract. Note that our system model feature data writes originated from off-chain (modeling data feeds in real smart contracts) and data reads originated from on-chain (modeling computation-oriented smart contracts). This is different from the models adopted in related research works [40, 34] where both data reads and writes originate off-chain. We believe our model better present the real-world use pattern of smart contracts and will demonstrate how it benefits domain applications in our case studies.

GRuB runs three system modules for dynamic data replication: 1) A workload monitor that monitors the trace of data reads and writes, 2) an online decision-maker that, based on the current workload trace, makes the decisions w.r.t. whether individual data records should be replicated onto the Blockchain, and 3) an actuator which executes the replication decision. Naturally, one can map existing dynamic-replication mechanisms [25] to this framework and tailor them to the case of smart contracts. In this design process, we identify two technical challenges:

First, existing dynamic replication schemes are designed to optimize communication costs in a distributed system, which causes suboptimal Gas in our problem setting. Specifically, existing schemes commonly collocate a decision-making module with the data replica in the effort to save communication costs. In smart-contract data storage, however, this design would mean collocating the workload monitoring with the data replica on the Blockchain, which incurs a large volume of on-chain storage writes (e.g., to maintain and update the workload trace) and thus leads to high Gas. Instead, GRuB places both the workload monitor and decision maker off the Blockchain for lower Gas. The DO and SP jointly monitor the workload trace and run the decision maker. To prevent the untrusted SP forging a workload trace, we propose a security protocol to run between DO and SP that verifies the trace integrity with minimal involvement of Blockchain for low Gas (§3.3.1).

Second, existing online algorithms for dynamic replication are designed without Gas awareness. In GRuB, we model the Gas by the number of most Gas-consuming operations in a smart contract and design online algorithms configurable with this Gas model. Through algorithm analysis, we prove that the Gas-aware online algorithms achieve bounded “competitiveness”, that is, the Gas costs of the online algorithms in the worst case are bounded by a small constant with comparison to an optimal offline algorithm (§3.3.2).
storage contract jointly provide a trustworthy service (i.e., GRuB) to serve data updates from DO and data reads initiated by the data users. GRuB is also an extensible storage service supporting application-specific smart contracts via callback functions.

The data model is a key-value dataset (KV dataset) consisting of data records sorted by data keys. Each KV record, say \( \langle k, v \rangle \), contains an identifying data key \( k \) and a data value \( v \). The KV dataset is stored in GRuB as follows: The primary data copy is stored in a KV store at SP and a full (or partial) replica of this KV dataset is stored on the storage contract. The GRuB exposes the following KV-store interfaces to serve data writes and reads.

\[
\begin{align*}
\text{Yes/No} &= \text{PUTS}(\{(k, v)\}) \\
q(\{k, v\}) &= \text{GETQ}(k, q) \\
q(\{k, v\}) &= \text{SCANQ}(k_1, k_2, q)
\end{align*}
\]

The DO produces data writes to the KV dataset and submits the data writes through a PUTS call. The data write in a PUTS call can be interpreted as an insertion of the record, an update, or a deletion.

Note that a DO’s function call includes multiple data updates or a batch of updates. The batched interface is suitable for the application where DO generates individual data updates continuously and in high frequency. Also with the batched interface, DO can interact with the Blockchain periodically. Sending an individual data update in a dedicated transaction to the Blockchain is not only wasteful in Gas cost but also unnecessary in that it includes multiple transactions in one Blockchain block.

A data user interested in a query of the KV dataset sends a SCANQ or GETQ request to the GRuB where it specifies the predicate of relevant KV records (e.g., range \([k_1, k_2]\) in a SCANQ call). In addition, the data user can specify the query \( q \) she is interested in over the relevant KV records.

The actors in our system, including DO, data users and SP, are identified by their public keys. We assume an external PKI style service (public key infrastructure) is there to securely store the bindings between identities and public keys, and to securely distribute keys in the beginning. To pay for the transactions sent in the protocol, DO sets up a cryptocurrency account. DO also sends allowance in this account to SP for her to pay for the transactions sent by SP.

During the protocol, the SP serves data reads and she can charge the standard cloud-service fee from there. The cloud service fee can be charged on demand, based on a standard pay-as-you-go model.

### 2.1.1 Target Applications

This system model supports various domain applications in modern log processing. As will be elaborated on, it can support high-frequency token trading in cryptocurrencies (§4.3.2) where DO is a token owner, say issuing transfer() calls [1], who transfers her tokens to another owner in return for other assets being transacted. A data user is also a token owner interested in checking her account balance (e.g., by issuing balanceOf() calls). For another instance (§4.3.1), it can support transparency-log auditing where a data owner is the log collector, a data user is a public log auditor, and a query written in the application contract carries out log auditing over relevant log entries.

### 2.1.2 Threat Model and Security Measures

In our system, DO, data users and the two smart contracts on the Blockchain are trusted. SP is the only untrusted party. In practice, the SP is operated by a for-profit company and can be malicious either intentionally (e.g., bribed or controlled by an insider) or unintentionally (e.g., compromised by a remote hacker). A malicious SP can mount attacks and present incorrect query results to data users: She can forge a data record in a query result that is not originally updated by DO (breaking the query integrity), omit or replay a valid data record (breaking query freshness and completeness).

In the presence of a malicious SP, this work aims at protecting data integrity, query completeness and freshness. As will be described in §4 we use an authenticated data structure, such as a Merkle tree, between the untrusted SP and trusted storage contracts. Next is the trust model of Blockchains and smart contracts in our system.

The Blockchain system is trusted under the standard assumption that majority of Blockchain nodes honestly follow the Blockchain protocol (honest majority) and 51% attacks are hard. The two smart contracts running in the Blockchain are also trusted in the sense that they are free of security bugs to exploit. In practice, there are attacks against a Blockchain system/network and smart contracts including smart contract exploits (e.g., reentrancy bugs and DAO attacks [1]), transaction exploits (e.g., distributed denial of service attacks), attacks on consensus protocols (e.g., selfish mining [23]), P2P network attacks (e.g., eclipse attacks [24]). This work does not address these attacks, but instead assume that external techniques can be employed to defend them, such as smart-contract verification [27].

### 2.1.3 Cost Model

The cost considered in this work is the Gas cost paid for Blockchain to run smart contracts and process transactions. We consider Ethereum as a representative extensible Blockchain supporting smart contracts. Each operation defined in a smart contract is associated with certain Gas units. Recall Table 1 lists five cost-dominant operations required in our system. In a smart contract, each operation is related to one or multiple data words, each of 32 bytes. The cost of an operation is a function of \( X \), the number of words involved in the operation. For instance, sending a transaction of \( X \) words costs the Gas units: \( C_{\text{tx}}(X) = 21000 + 2176X \). Writing \( X \) words to the smart-contract storage costs \( C_{\text{insert}} = 20000X \) Gas units, if the write is an insertion, or \( C_{\text{update}} = 5000X \) units, if the write is an update of existing words. Reading \( X \) words from the smart-contract storage costs \( C_{\text{read}}(X) = 200X \) units. Computing the hash of \( X \) words stored in the memory costs \( C_{\text{hash}}(X) = 30 + 6X \) units. It is clear that the most expensive operations in a smart contract are due to transactions and on-chain storage writes.

### 2.2 Research Statement

Consider the storage contract in our system that serves data updates from the off-chain DO and data reads for the on-chain application contract. The research goal of this work is to reduce the Gas cost of the storage contract without losing security.

### 2.3 Design Motivation: Why Replicate Data on Blockchain, Dynamically?

To motivate our proposed study, dynamic data replication, we first describe the baselines of static data replication in Blockchains.

**Baseline BL1:** Always replicating data onto the Blockchain:

In this scheme, the storage contract maintains a full replica of the KV dataset. Each data update from DO would require embedding the KV record to be updated in a transaction (costing transaction fees) and issuing contract-storage writes to persist the update on the Blockchain (costing contract-storage writes). Each data read to serve the application contract can be processed by a contract-storage read (costing contract-storage reads). Recalling the Gas cost model in Table 1, BL1’s cost is dominated by the transaction fees and contract-storage writes on the write path.
Baseline BL2: Never replicating data onto the Blockchain:

In this scheme, the storage contract maintains no replica of the KV dataset. A batch of data updates from DO are digested and it is the hash digest that is included in the transaction (i.e., amortized transaction fees). Each data read to server the application contract has to be processed by sending transactions from the off-chain SP (costing the transaction fees). Recalling Table 1, BL2’s cost is dominated by the transaction fees on the read path.

In our changing read/write patterns, a static replication scheme, be it BL1 or BL2, has to pay the high Gas cost when the workload becomes inapt. For instance, BL1 cannot avoid the high Gas cost when the workload becomes write intensive, and BL2 cannot avoid the high Gas cost when the workload becomes read intensive.

The above illustrates the limitation of static replication baselines in serving workloads of changing access patterns. To further motivate a dynamic replication scheme, we are to justify that the cost benefit brought by such a dynamic scheme outweighs the associated overhead. Concretely, unlike the static replication schemes, a dynamic replication scheme has overhead in monitoring the workload and making replication decision, dynamically. Therefore, if the benefit brought by dynamically switching replication decisions is lower than the overhead, it is not worthwhile to replicate data dynamically.

The key observation motivating this work is that the cost difference between data replication and no replication schemes is large, which is due to Blockchain’s Gas cost model. To be more concrete, we use, as a metric to quantitatively motivate dynamic data replication, the cost difference between a replication scheme (BL1) and a non-replication scheme (BL2). The larger such a cost difference is, the more cost saving it brings by dynamically switching from replication to non-replication (and vice versa). By contrast, the risk of static replication is that it cannot switch to a better replication decision, w.r.t. the current workload, and has to pay a large cost disparity between different replication options.

To validate the observation, we conduct a back-of-the-envelope calculation and a preliminary measurement study:

- Consider an example scenario of serving one million 32-byte long data records with a binary Merkle tree about 20 levels deep. In the target workload, assume 1000 data updates are batched in one digest update on the Blockchain. Here, the size of data batch is set (at 1000 data records) based on the target workload, such that on average, there is one digest update produced in one block of the Blockchain. Based on the limitation of transaction size in Ethereum, a transaction can hold up to 48 data records.

In the above setting, for the strategy that never replicates data, the Gas cost per data update is \( (C_{update}(1) + C_{digest}(1))/1000 \approx 26000/1000 = 26 \) units, as one digest update on Blockchain is amortized among 1000 data updates in a batch. The Gas cost per data read, due to transaction fees, is \( 21000/48 + 2176 + (1 + 20) = 46133 \); recall that a maximal transaction of 1000 words can hold 48 data records.

For the strategy that always replicates data, the Gas cost per data insertion (update) is \( 20000(5000) \) units. The Gas cost per data read is 200 units. It is clear that the data write cost of the replication scheme (BL1) and the data read cost of the non-replication scheme (BL2) are the cost bottlenecks. It can be seen in a write intensive workload, the replication strategy costs \( 1000 \times \) more than the non-replication strategy. In a read-intensive workload, the non-replication strategy costs over \( 200 \times \) more than the replication strategy. Always sticking to one replication decision, without dynamically adjusting the decision, would risk the system experiencing either \( 1000 \times \) or \( 200 \times \) higher cost than the alternative decision.

- We conducted a preliminary measurement study by implementing the above two baselines on Ethereum. The experiment setting is the same as the above analytical setting (i.e., with one million data records). We drove workloads with varying read-to-write ratios and reported the Gas costs per read/write operations. The measurement result is illustrated in Figure 2. On the one hand, the result confirms a well-known fact that a data replica can reduce the read costs and it leads to lower write costs without replicating data. On the other hand, the result reveals that the cost difference between the two static-replication baselines is large.

Figure 2: Preliminary cost study: One million data records digested by a Merkle tree

Specifically, for a write-intensive workload, the replication scheme incurs a cost \( 100 \times \) higher than that of the non-replication scheme. For the read-intensive workload, non-replication incurs \( 7 \times \) higher cost than replication. In other words, a dynamic replication scheme can benefit from being able to switch to no data replication upon write-intensive workloads, saving costs more than 99% of a static replication scheme starting as BL1. The large cost difference can be explained by the unique Gas cost model: The cost difference between the two schemes, in a read-intensive workload (in a write-intensive workload), is attributed to transactions (on-chain storage writes), which are among the most expensive operations defined in a Gas cost model (recall Table 1).

2.4 Research Overview and Design Space

We formulate the dynamic data replication problem in the primary-copy model.

Preliminary: Primary-copy model and dynamic data replication: In a primary-copy model, a primary site stores the primary data copy and multiple secondary sites may store data replicas. A data write updates both the primary data copy and data replicas. A data read, submitted to a site, is served by a data replica on the site, if any, or by the primary copy. Online algorithms are run to decide whether a data record should be replicated on a secondary site, by monitoring the current workload: If a workload contains enough reads that can amortize the cost of updating a replica, it will decide
3. ADAPTIVE DATA REPLICA TION WITH BLOCKCHAIN

At a high level, the GRuB is a data-storage system consisting of a data plane and control plane. As shown in Figure 3a in the data plane, GRuB processes data reads/writes based on data-replication states, and it does so by managing the primary data copy stored off-chain and the data replica on the Blockchain. In the control plane, GRuB runs a framework that monitors the read/write trace, makes decisions on replication states and updates the states.

In this section, we describe the detailed GRuB system from the following three angles: the static data structures and system architecture (§3.1), the data plane (§3.2), and the control plane (§3.3).

Describing the system from each angle, we will include the security analysis. At last, we will present the implementation note of a functional prototype of GRuB.

3.1 Static Data Structures

The state of data replication is stored in our system by augmenting the KV records. Each KV record, say \( (k, v) \), is associated with a replication state \( s \), where the state can be either \( NR \) (i.e., not replicated on the Blockchain) or \( R \) (i.e., replicated on the Blockchain).

Recall that the SP maintains a KV store. The KV store on the untrusted SP is protected via an authentication data structure (ADS), which allows for trusted data updates and reads, and prevents the untrusted SP from forging the dataset. For the sake of simplicity, we use a binary Merkle tree to illustrate our system. The Merkle tree is built on top of the KV dataset with replication state. Specifically, the data layout on which the Merkle tree is built is the following: KV records are first grouped by the replication states and then they are sorted by data keys. This data layout allows the Merkle tree to serve the range query on \( NR \) data records, which is required in the data-read protocol in GRuB (§3.2.2). For instance, the four KV records in Figure 3b fall under two groups, the \( NR \) records (i.e., \( (k = w, NR, v = 100), (y, NR, 200) \)) and the \( R \) records (i.e., \( (x, R, 300), (z, R, 400) \)). In each group, KV data records are sorted by data keys and a Merkle tree is built on top of the two groups of KV records as in Figure 3c.

3.2 Data-Plane Protocols

3.2.1 Data Writes

On the write path, DO continuously produces data writes to update the KV dataset. It needs to update both the primary copy stored on SP and the replica stored on the Blockchain. The data writes should be persisted, to one or two data copies, securely against the untrusted SP. To achieve these goals, the data-write protocol in GRuB entails the following steps, which are also illustrated in Figure 3d.

\( \text{w1} \) Given a data write, DO interacts with SP in an authentication data structure protocol to securely update both \( R \) and \( NR \) KV records stored on SP. With a binary Merkle tree, it entails that SP sends a Merkle proof to DO, who updates the Merkle root hash (or digest) locally. Specifically, given a write on KV record \( (k, v) \), the Merkle proof is the Merkle tree nodes surrounding the path from the leaf of this KV record to the root. An example will be shown in the next paragraph. The DO receiving the proof verifies it against its current root hash, and then updates the root hash based on the new KV record \( (k, v) \).

\( \text{w2} \) At the end of every epoch, DO batches data writes on replicated KV records. It sends the batched writes and the latest digest in a transaction to the Blockchain. The storage contract on the Blockchain exposes the following contract function:

The storage-management contract processes the write request to update the copy of digest on the Blockchain and
The proof is the Merkle proof that the DO retrieves from SP is the con-

In the end of every epoch, DO also collects the operation trace and runs a control framework (in §3.3) to dynamically update data-replication states. Concretely, DO collects the trace of data writes locally, and the trace of data reads from SP (see Figure 3b). It will then feed the traces as input to the control framework which produces the output of updated replication states.

The state transitions are incorporated into the transaction sent in \( w_2 \) (recall Figure 4). The storage-management contract processes state transition \( NR \rightarrow R \) by inserting the data replica to the buffer in the contract. It processes state transition \( R \rightarrow NR \) by invalidating an existing replica in the contract buffer.

**Examples:** Suppose DO produces one data update in an epoch, \( (u, 110) \). The initial state of the system, illustrated in Figure 3c, is that the record is not replicated, \( (u, NR, 110) \). Assume in Step \( w_4 \) the control framework does not update replication state. In Step \( w_3 \), the Merkle proof that the DO retrieves from SP is \( h_3, h_4 \). After verification based on the proof, she then updates the KV record from \( (u, 100) \) to \( (u, 110) \). She also computes the new hash \( h'_4 = H((u, 110)) \) to replace the old \( h_4 \). The new root hash is calculated \( h'_5 = H(h_3||h'_4) \) where \( h'_2 = H(h'_4||h_2) \). In Step \( w_2 \), the transaction sent to the storage contract contains the new root hash \( (h'_5) \), and nothing else (due to no state transition or no update on replicated records).

For another example, suppose DO produces one data update \( (x, 310) \) against the same initial state in Figure 3c. Here, the original record is replicated, \( (x, R, 300) \). Assume in Step \( w_4 \) the control framework will update the replication state from \( R \rightarrow NR \) (e.g., by a memoryless decision-making algorithm that will be described in §3.3.2.1). The state transition triggers the KV record to be relocated, that is, leaving the group of \( R \) records and joining the group of \( NR \) records. In Step \( w_7 \), the proof is the Merkle proof of its current location (i.e., \( h_2, h_7 \)) and that of its new location. The new location is between records \( (x, NR, 100), (y, NR, 200) \) and the proof of the new location includes \( h_3 \) and these two records. DO verifies the integrity of the original record using the proof against its current digest. DO then relocates the KV record (due to new replication state) and produces the new root hash. This is done by marking the original KV record invalid (i.e., \( h'_8 = H((x, R, 300), invalid) \)), and by updating the Merkle tree with \( h'_3 = H(h'_9||h_7), h'_5 = H(h_2||h'_4) \) and by inserting the new KV record at the new location (i.e., \( h_8 = H((x, NR, 310)), h_9 = H(h_4||h_3), h'_2 = H(h_9||h_5), h'_4 = H(h'_2||h'_4)) \). In Step \( w_8 \), the transaction sent by DO includes the new root hash \( h'_9 \), the KV record with a state transition, namely \( (x, NR, 310) \). The storage contract receiving the transaction will invalidate the replica of the original record, \( (x, R, 300) \).

### 3.2.2 Data Reads

In the read path, a data user is interested in the result of a database query with a specific predicate \( q \). She sequentially sends the query to SP and Blockchain to obtain a trusted query result. The data-read protocol for trusted query processing is described below. The steps are also illustrated in Figure 4b.

A data user sends to the SP a query predicate \( q \) and her signature signing the query. Here, the predicate can be a point- or range-query on data keys, supported by KV-store operations (i.e., \( GET \) or \( SCAN \)). As mentioned in §2.1, the query can be extended to include computation logic on top of the predicate, such as group-by aggregation.
The SP evaluates the query over $NR$ KV records. It translates the query to GETQ or SCANQ, depending on the predicate, and retrieves $NR$ KV records that match the query. SP also prepares the query proof from the Merkle tree. The proof consists of the Merkle authentication paths surrounding the $NR$ records.

The SP sends the $NR$ records matching the query and the query $q$ itself to the Blockchain. The storage contract receiving the transaction will verify the integrity of $NR$ records and then triggers the query-processing contract to process the query by accessing the retrieved $NR$ records and the $R$ records replicated on the Blockchain.

Example: Suppose the system initial state is illustrated in Figure 3c and a data user sends a range query $q = [x, z]$ in 2a. In Step 3b, SP evaluates the range predicate and produces the following $NR$ records that match the query: $(y, NR, 200)$. The Merkle proof is $h_7$, $(w, NR, 100), (x, R, 300)$. In Step 3b, the storage-management contract verifies the integrity and completeness of $NR$ records using the proof against the digest stored on the Blockchain.

3.2.3 Protocol Analysis

In our protocol, there are several query-authenticity properties: query-result integrity completeness and freshness. Formally, the query integrity requires that the KV records in a query result are the original records updated by DO. In other words, there should not be a single KV record in the query result that is forged by the malicious SP. Given a range query (e.g., SCANQ), the query completeness requires that all KV records that match the range query are included in the result. In other words, there should not be a single KV record matching the query that is omitted in the result. Assuming that there is a global clock, the query freshness states that any KV records, that match the query predicate and that are updated after the query is submitted, should be included in the query result. In other words, there should not be a single correct KV record (correct in the sense of matching the query predicate and being updated after the query is submitted) that is omitted in the query result. To distinguish query completeness from freshness, we require that a query result of completeness includes only the KV records that are updated one epoch before the query submission time.

The protocol correctness states that given a benign SP following the protocol execution, the query result of a GETQ or SCANQ has integrity, completeness and freshness. Analyzing the protocol correctness in integrity and completeness is straightforward as a benign SP follows the protocol execution to retrieve the KV records of integrity and completeness. The query freshness can be achieved when the benign SP includes the latest matching records in the result.

The protocol security states that given a malicious SP who do not follow the read/write protocol, the result of a GETQ or SCANQ has integrity, completeness and freshness if the KV records in the result are verified by the storage contract.

3.2.3.1 Data Freshness.

In our protocol, because of the Blockchain’s native write delay, the system does not provide the security in query freshness or security in strong consistency. Instead, it guarantees “epoch-time-bounded” freshness of query results. Conceptually, a query result includes all the KV records that are updated one epoch before the query submission time. Formally,

**DEFINITION 3.1 (EPOCH-BOUNDED DATA CONSISTENCY).** Given a query (SCANQ or GETQ) submitted at time $t$ and epoch time $E$ in which DO sends data updates, it is guaranteed that the query result includes all the matching KV records updated before $t - E$. We call this property by Epoch-bounded data consistency.

Data freshness analysis: In our protocol, data flows from the trusted DO, SP and Blockchain, to the data users. Recall that DO sends data updates in batches and in epoch where each epoch takes $E$ time units. The Blockchain receives digest-update transactions every epoch and verifies the query results using the latest digest. Blockchain provides the property that it finalizes a recently sent transaction in $F$ blocks (meaning that the state whether the transaction is included in the Blockchain is determined with consensus among all Blockchain full nodes after $F$ blocks).

In this setting, a malicious SP who wants to break query freshness may omit the KV records that are updated recently. To be precise, considering a query submitted at time $t$, there are two cases: 1) The KV record omitted is updated before $t - B \cdot E$. 2) The KV record omitted is updated after $t - B \cdot E$. For Case 2), the digest update that reflects the omitted KV record in the query result may not be finalized on all Blockchain nodes. Thus, a malicious SP can simply provide a proof against a previous digest (or equivalently a previous snapshot of a KV dataset that does not yet include the data update) to the Blockchain and pass the verification.

For Case 1), the digest update that reflects the omitted KV record must be sent to the Blockchain at the time $t - B \cdot E$. At the time $t$, the digest stored on all Blockchain nodes must reflect the KV record. When the SP omits the KV record in the query result, the storage contract’s verification using the digest can detect the omission. Otherwise, the SP has to generate a non-membership proof of a KV record that does exist under the digest, in order to successfully pass the verification. Forging such a proof is as hard as finding a cryptographic hash collision, which is unfeasible to probabilistic polynomial time (PPT) adversaries (SP). For instance, in Figure 3c, forging a non-membership proof for KV record $(y, NR, 200)$ requires finding another record, say with data key $v$, whose hash is equal to $h_5$, namely finding a hash collision with record $(y, NR, 200)$, which is computationally hard.

3.3 Control Plane: Online Replication Decisions

GRuB’s control plane takes as input the read-write trace and produces as the output data-replication decisions. As shown in Figure 3b, the control plane works in three steps: A monitor that captures the trace of reads and writes on the data plane, a decision-maker that runs online algorithms to make data-replications decisions based on the trace from the monitor, and an actuator that takes actions to materialize new replication decisions produced by the decision maker. The actuator updates the data-replication states of individual records and affect the read/write paths in the data plane (e.g., steps 3a and 3c).

A baseline design is to materialize the control plane directly on the Blockchain. That is, the Blockchain runs the three steps mentioned above to make replication decisions. However, storing the trace of reads and writes on the Blockchain incurs a large number
of on-chain storage writes, which leads to high Gas cost of running the control plane itself. Thus, we focus on placing the control plane off the Blockchain and on the trusted DO, as in Figure 3b.

We identify two challenges in the above design: 1) The input trace of data reads originate from the untrusted SP, and it is a challenge for the untrusted SP to provide an authentic read trace. 2) The conventional online replication algorithms which optimize the communication cost do not necessarily optimize the Gas cost. We propose two techniques in the control plane: Secure read trace feeding by untrusted SP (§3.3.1), and Gas-aware online decision making (§3.3.2).

### 3.3.1 Authentic Read Trace by Untrusted SP

**Design rationale:** Given that the data reads originate from the untrusted SP, a naive approach is for SP to provide the read trace to DO running the control plane. However, SP is well motivated to forge a read trace – By forging a read trace and by misleading DO not to replicate data, SP can serve more \( NR \) records, from which she can benefit. SP can charge certain cloud-service fees for each \( NR \) record she served (recall the cloud service model in §2.1).

To prevent SP forging the read trace, one can require the Blockchain to validate the read trace provided by SP (named Baseline BL3). Specifically, the storage contract logs the data reads in Step 2. When DO submits newly produced replication decisions, the storage contract checks the equality between the read trace provided by SP and the read trace previously logged. However, this design requires the Blockchain to store every read it served which may cause high Gas costs (See §5.1 for our evaluation results).

**Proposed design:** In the proposed design, the storage contract additionally maintains a hash digest, \( ha \). Given a GETQ query, \( ha \) digests all the off-chain read operations in serving the query. In an epoch, \( ha \) digests the \( ha \) of all the GETQ queries submitted in the epoch. When serving a GETQ query, as in Step 2, the storage contract builds the \( ha \) of the query and uses it to update the \( ha \).

In terms of the Gas cost, this design does not require storing the read operations on the Blockchain, but instead a single digest updated once for every GETQ. The cost is expected to be lower than that of baseline BL3.

**Security:** SP can forge the trace of read operations, such as modifying, omitting and replaying an operation. However, any forging will be detected by the mismatch with the digest on Blockchain (namely \( ha \)). The integrity and completeness of the read trace is protected by \( ha \).

### 3.3.2 Gas-aware Online Decision Making

The key component in the control plane is the online decision maker. Commonly, such online algorithms are designed based on the following intuition: Given a KV record and a trace of data reads/writes, it runs an online algorithm that estimates the cost of two alternative plans, namely to replicate the record and not to replicate, and picks the plan with the lower cost as the output. In the following, we present the proposed online algorithms for decision making: an online algorithm that resets its memory upon each write (i.e., memoryless algorithm) and an online algorithm that remembers the operation history.

#### 3.3.2.1 Memoryless Algorithm.

The memoryless algorithm for replication decision making is described in Algorithm 1. Recall that each data record is associated with a state, either \( R \) or \( NR \). The algorithm takes as input the trace of reads on data records of \( NR \) (provided by SP) and writes on any records (provided by DO locally). The algorithm maintains a list of counts, each for a \( NR \) record. The counter counts the number of consecutive reads on the data record that are received since the last write. The algorithm iterates through the read/write trace. Upon a write on a record, say \( (k,v) \), the algorithm resets the counter of record \( (k,v) \) back to zero and updates the record’s \( NR \). Upon a read on a \( NR \) record, it increments its counter. When the counter reaches a preset parameter, \( K \), the algorithm changes the record’s state from \( NR \) to \( R \) and removes the data record from the list of counts.

**Setting the parameter:** The algorithm is parameterized by \( K \). In practice, the value of \( K \) is set to the cost ratio of updating a byte on Blockchain to reading a byte off-the-Blockchain.

\[ K = \frac{C_{\text{update}}}{C_{\text{read off}}} \]  

**Algorithm 1 Replication Memoryless(ops, count, states)**

| Input | read/write operations ops, read count count, and the replication states states |
|-------|---------------------------------|
| Output | updated replication states states |
| 1:    | for all \( o \in \text{ops} \) do |
| 2:    | if \( o\text{.isWrite()} \) then |
| 3:    | \( \text{count}[o\text{.key}] = 0 \); |
| 4:    | \( \text{states}[o\text{.key}].set(NR) \); |
| 5:    | else |
| 6:    | if \( \text{count}[o\text{.key}] < K \) then |
| 7:    | \( \text{count}[o\text{.key}] += 1 \); |
| 8:    | end if |
| 9:    | if \( \text{count}[o\text{.key}] \geq K \) then |
| 10:   | \( \text{states}[o\text{.key}].set(R) \); |
| 11:   | else |
| 12:   | \( \text{states}[o\text{.key}].set(NR) \); |
| 13:   | end if |
| 14:   | end if |
| 15:   | end for |

In workloads that are read intensive, supporting \( K < 1 \) is essential. We add an optional extension to Algorithm 1. When \( K < 1 \), the memoryless algorithm tosses a dice when encountering a write operation, and probabilistically determines whether to replicate upon the write. Precisely, given \( K < 1 \), the algorithm results in a replication decision \( R \) with probability \( 1 - K \). For instance, if \( K = 0.3 \), there is a 70% chance that the algorithm decides to replicate data upon a write. If \( K = 0 \) (or \( K = 1 \)), there is 100% (or 0%) chance for a replication decision, which is consistent with the original algorithm.

**Algorithm analysis:** As will be analyzed in Appendix §X, the memoryless algorithm in Algorithm 1 with parameters configured in Equation 2 is \( 2 \)-competitive.

#### 3.3.2.2 Memorizing Algorithm.

In practice, workloads exhibit temporal locality and include repeated sequences of read/write operations. The memoryless algorithm does not remember the past decision made for a repeated operation sequence and would lead to wasted efforts towards making the same decision.

We propose a memorizing algorithm that exploits the temporal locality in workloads by memorizing the decisions made for similar operations in the past. The memorizing algorithm takes as input the trace of reads and writes. Note that unlike the memoryless algorithm, the memorizing algorithm takes in the trace of on-chain data reads.

The algorithm, described in Algorithm 2, maintains two counts for each data record, \( \text{readCount} \) and \( \text{writeCount} \). \( \text{writeCount} \) increments when the algorithm, iterating through the read/write trace, encounters a read (write) operation. The algorithm checks two conditions upon each read/write operation: If the condition holds, \( \text{writeCount} * K' + D \leq \text{readCount} \), the...
Algorithm 2 Replication_Memorizing(ops, readCount, writeCount, states)

Input: read/write operations ops, read counts readCount, write counts writeCount and the replication states states
Output: updated replication states states

1: for all o ∈ ops do
2:   if o.isWrite() then
3:     writeCount[o.key] += +;
4:   else
5:     readCount[o.key] += +;
6:   end if
7:   if writeCount[o.key] * K’ + D <= readCount[o.key] then
8:     states[o.key].set(R);
9:   end if
10:  if writeCount[o] * Y > readCount[o.key] then
11:     states[o.key].set(NR);
12:  end if
13: end for

record’s state is updated from NR to R. It also resets writeCount to zero and reduces the value of readCount to D. If the condition holds, writeCount + K’ - D >= readCount, the record’s state is updated from R to NR. It also resets readCount to zero and reduces the value of writeCount to D/K’.

Parameter setting: Similar to the memoryless algorithm, parameter K’ is set to the ratio of on-chain write cost to off-chain read cost, K’ = Cwrite/Creadoff. The other parameter D determines how sensitive the replication state is to the workload. A small D leads to frequent changes of replication state, while a large D leads to a stable setting of replication state.

Algorithm analysis: As will be analyzed in Appendix §A, the memorizing algorithm in Algorithm 2 is \(4D+3\)-competitive.

Executing the algorithm: Unlike the memoryless algorithm, the memorizing algorithm cannot be executed purely off the Blockchain, because the algorithm input includes the on-chain reads, which are only visible to the Blockchain. Instead, we propose partitioning the algorithm in two parts and running them respectively on and off the Blockchain. The off-chain algorithm runs on DO and takes the partial input (the trace of data writes and off-chain data reads); this is similar to the case of memoryless algorithm. The off-chain algorithm conducts an “early” check on the read/write count for setting the replication state to R. It then sends the count and early-check results to the Blockchain, where the on-chain algorithm additionally takes the input of the on-chain read trace and refines the check results.

4. SYSTEM DESIGN, IMPLEMENTATION AND CASE STUDIES

4.1 System Design

We present a design of GRuB as a distributed middleware system running across data owners (DO), data users (DU), a cloud service provider (SP) and a public Blockchain. As illustrated in Figure 5, the GRuB distributed system consists of four major components: Two clients respectively for interacting a data owner (DO) and a data user, a SP-side middleware running on top of a KV store, and a storage contract running on the public Blockchain. Together, GRuB, as a whole system, provides application interfaces: Puts called by DO, Get called by a data user, and an application-specific contract called back by the storage contract.

Concretely, GRuB supports two clients: 1) A client running on the data owner (DO) exposes the interface of batched data write, Puts. The DO client translates a Puts call into a) a series of Puts call to the KV store, in order to update the primary data copy there, and b) a smart-contract call of function storage_write().

Figure 5: GRuB distributed system: The system includes data owner (DO), data users, cloud service provider (SP) and the Blockchain. GRuB is the storage layer of the system, which accepts the data-write requests (i.e., Puts) from DO and the data-read requests (i.e., GetQ) from a data user. Internally, GRuB persists a KV dataset on SP and manages such data through the storage contract on the Blockchain. GRuB is extensible to support rich queries written in an external application contract. The GRuB system is designed in such a way that encapsulates the most expensive operations in Gas, namely storage updates in smart contracts and transactions.

defined in the storage contract, which updates the replicated data records on the Blockchain. 2) The other client running on the data user exposes the interface of data-read query, GetQ. The data-user client translates a GetQ call by the data user into a RPC into the KV store middleware. The KV store middleware then issues a Get request to the underlying KV store to retrieve data records matching the queried predicate, and prepares the contract call for function SRead(). Through the SRead() call, data records that are not replicated but are matching the query are sent to the storage contract. The storage contract then adds the replicated data records that match the query before relaying the control flow to the application-specific contract. The application contract evaluates the query based on the data records presented by the storage contract.

The control plane of the GRuB is implemented on the client side where the monitor collects the trace of GetQ and Puts and runs a decision-making algorithm (as described in §4.1). The actuator updates the data-replication states maintained inside the clients. In our evaluation, the trace of Puts and GetQ is generated from YCSB.

The GRuB system is designed to be extensible: The APIs exposed by the GRuB are defined in Figure 5. By Puts(KV[]kvs), a DO application code writes multiple KV records in a batch (i.e., kvs) to the GRuB. By GetQ(k1,k2,q), a data user queries the dataset stored in GRuB: Currently, GRuB supports query logic q with point or range predicates on data keys (e.g., k1 and k2). The application contract implements a function EvalQ(KV[]kvs, Queryq). The storage contract prepares the complete and fresh set of KV records matching the range predicate (i.e., kvs), and invokes the EvalQ function on the application contract.

4.2 Prototype Implementation
We present a prototype implementation of GRuB, functional with Ethereum Blockchain and a Google LevelDB instance for the KV store on SP. While we present one prototype in this paper, the system design of GRuB is generalizable to any cloud-storage service exposing a KV store interface (e.g., Amazon S3) and an IaaS cloud service allowing user-deployed code (e.g., Amazon EC2).

In our prototype, the major components of GRuB, including the KV store middleware and the two clients for DO and data users, are implemented in Python. In particular, the KV store middleware relies on a Python binding for the underlying LevelDB. The two GRuB clients in Python interact with the Ethereum client, geth. To make GRuB functional with a real Ethereum network (e.g., the Ropsten testnet or mainnet), we use the following settings: 1) An epoch in GRuB is set to be a multiple of the block time of Ethereum (i.e., every 10 ~ 20 seconds, a new Ethereum block is found on average). 2) We use the suggested transaction fee (e.g., 21000 Gas) and Gas price (i.e., 2 GWei) in our evaluation (in both §4.3 and §5), which we found are practical in interacting with Ethereum Ropsten testnet. In the more adversarial environment, such as the case of network partition, DoS attacks or transaction volume spike, one may need to increase the transaction fee and Gas price, which is out of scope in this paper.

## 4.3 Case Studies

### 4.3.1 Blockchain-based Log Auditing

Transparency logs, as a system-accountability measure, become increasingly popular in modern InfoSec applications, such as web certificate transparency (CT) [3][2], key transparency [30], supply-chain transparency. Making the system logs public auditable (or transparent) is critical to the timely detection of anomaly events in the log (e.g., misissued certificates in CT). In existing schemes, including the recent Blockchain logging [15], it is required that a log auditor has to download a copy of the full log for auditing. This is cumbersome for low-end clients (e.g., in web and mobile computing). GRuB allows to delegate the heavyweight log auditing to the Blockchain at low Gas.

```python
1 // Off-chain DO extension
2 void IssueCert(Cert cert){
3     localKV.push(cert.hostname, cert);
4     if (time - lastEpoch > epochSize){
5         GRuB.Puts(localKV);
6     }
7     localKV.clear();
8 }
9 }
10 // Off-chain data-user extension
11 void AuditCert(String hostname, Cert[] localCerts){
12     GRuB.GetQ(hostname, SHA256(localCerts));
13 }
14 }
15 // On-chain application contract
16 bool EvalQ(Cert[] matchCerts, HashDigest d){
17     return SHA256(matchCerts) == d;
18 }
```

Figure 7: Application contract supporting CT log auditing

We build a GRuB application for CT logs. The world of CT logs can be mapped to the world of GRuB in the following manner: In a CT log, CAs issue web certificates logged to a CT log server and domain owners audit the CT log to detect any misissused certificate by rogue CAs. In the GRuB-based CT log, as illustrated in Figure 6a the CT log server is materialized in GRuB, the CA plays the role of data owners (DO). The domain owners play the role of data users in GRuB. The data of CT log is modeled as a KV dataset where a KV record is a web certificate with data key being the hostname and value being the certificate itself.

We implement this CT-log application by two GRuB client extensions and an application contract. 1) The DO extension supports certificate issuance (i.e., IssueCert(cert) in Figure 7): For each issued certificate, the extension verifies it against the issuing CA's public key and batch it with other certificates before invoking a Puts call to store them in GRuB. 2) The data-user extension supports a domain owner audits her certificate of interest (i.e., AuditCert(cert) in Figure 7). It translates each certificate audit request into GRuB API GetQ(). The application contract supports auditing the certificates of given hostname.

**Cost evaluation:** In our case study, we populated 100,000 real CT certificates [8] into GRuB. The total cost is $11883136. Given the Ether price $168.52 (as of Aug. 30, 2019) and the standard Gas price 2 GWei per unit, the cost is 0.024 Ether = $4.0448 USD. A CT log server today [8] contains about 4.5 millions CT certificates. Thus, the cost of launching a full CT log server using GRuB is 1.07 Ether or 180 USD.

For comparison, we populated the same 100,000 certificates into the scheme without replication (BL2) and with replication (BL1). 1) BL1 costs 235, 200, 000 Gas (for 100,000 certificates) or 79.34 USD. In other words, the BL1 cost for a full CT log server of 4.5 million certificates is about $35672.31 USD. 2) BL2 under this write-only workload serves as an ideal approach. BL2 costs 11, 531, 136 Gas, or $3.89 USD for 100,000 certificates. For launching a full CT log server, BL2's cost is about $174.89 USD.

### 4.3.2 High-Frequency Trading at Low Gas

Token is one of the most common smart contracts. In Ethereum, for instance, about 30% of deployed smart contracts are token contracts that follow the ERC20 standard. Most existing ERC20 token contracts are written in such a way that the token states (e.g., account balances) are stored on the Blockchain, that is, BL2. This incurs high Gas, when they are used to support real finance applications in high-frequency token trading. GRuB allows to support high-frequency token trading at low Gas.

---

**Figure 6:** GRuB applications

In this section, we present how GRuB can be used in two real applications. The focus of case studies is to demonstrate the practicality of GRuB in terms of how much USD is needed to launch GRuB based domain applications. We leave to the evaluation of GRuB’s Gas saving from the two baselines to §5.
1 // Off-chain client extension
2 void DOTransfer(address from, address to, uint tokens) {
3     balanceFrom = GetQ(from);
4     balanceTo = GetQ(to);
5     if (balanceFrom >= tokens) {
6         localKV.push(from, balanceFrom - tokens);
7         localKV.push(to, balanceTo + tokens);
8     }
9     if (time - lastEpoch > epochSize) {
10        GRuB.Puts(localKV);
11        localKV.clear();
12    }
13 }
14
15 // On-chain application contract
16 uint DUBalanceOf(address owner) {
17     balance = GetQ(owner);
18     return balance;
19 }
20
21 // Off-chain application contract
22 uint EvalQ(unit balance) {
23     return balance;
24 }

Figure 8: Application contract supporting ERC20 tokens

We build a GRuB application for high-frequency token trading. The world of token trading is mapped to the GRuB system model in the following manner: In high-frequency trading, token owners submit a series of token functions (e.g., transfer(), approve, balanceOf, and other ERC20 functions) to a delegation service, who batches and relays the requests to the token contract. In GRuB-based token trading, the GRuB hosts the token contract (with off-chain token state and dynamic replication). The delegation service plays the roles of both data owner (DO) and data user in GRuB: A typical token function needs to read-modify-update token contract state (e.g., transfer()).

Based on the above mapping, we implement an ERC20-compatible token system illustrated in Figure 8. The application consists of a GRuB client extension (for both DO and data users) and an application contract on-chain. The client extension run by the delegation service supports two ERC20 functions: DOTransfer() and DUBalanceOf() (see Figure 8). For DOTransfer(), the extension code validates it via GRuB call GetQ and then places it in the batch to update the token balances via Puts at a later time. For DUBalanceOf(), the extension code calls GetQ. The application contract simply implements an identity function to return the balance of a queried token owner.

Cost evaluation: We evaluate the cost of launching a GRuB-backed token system. We use the real workload trace: We collected the function-call history of BNB contract (the most popular contract by market cap on Ethereum) from the Etherscan.io website. From the trace, we replay about 9400 transfer() calls into GRuB. The cost is 976,521,609 Gas, or 1,935 Ether (based on the common gas price, 2 GWei per Gas), or 326.09 USD (based on the Ether price of the writing, $168.52 per Ether).

5. EVALUATION

This section presents the cost evaluation based on experiments. The goal is to evaluate the Gas cost of GRuB including both data-plane and control-plane costs. The experiments based evaluation complements the algorithmic analysis in §5 by presenting concrete cost numbers instead of just worst-case bounds. Specifically, the design of our experiments is to answer the following questions:

1. Whether and how fast will GRuB converge to changing workloads?
2. How sensitive is GRuB’s cost to the various parameters that GRuB exposes? Recall that relevant parameters include data settings (e.g., record size, data size), choice of the algorithm, algorithmic parameters, etc.

Experiment overview: In our evaluation, we use two types of workloads: a synthetic workload and the industrial-strength workload generated by Yahoo Cloud Serving Benchmarks (YCSB [29]). The synthetic workload is generated under a controlled manner (the workload parameters and generation will be described). The purpose of the synthetic workload is to create microbenchmarks to evaluate the cost of GRuB under different settings and parameters.

5.1 Converged Gas under Repeating Workloads

In this section, we evaluate the Gas of GRuB under repeating workloads. With repeating workloads (i.e., assuming the read-write pattern repeats sufficient times), GRuB will make consistent decisions eventually and the Gas will converge. Our goal here is to evaluate the converged Gas of GRuB under different factors.

In this set of experiments, the workload is synthetically generated which consists of repeated sequences of reads and writes under a given ratio (e.g., two reads and one write for read-to-write ratio 2).

5.1.1 Sensitivity to Read-to-Write Ratio

In this experiment, we evaluate the Gas with different read-to-write ratios. For comparison to GRuB, we consider both baselines of static data replication (i.e., BL1 and BL2). In addition, we consider the two baseline designs for dynamic data replication that respectively store on the Blockchain, the trace of reads and writes, and the trace of reads. In each experiment, we drive the synthetic workload of a specific read-to-write ratio to the system and measure the total Gas. We report the average Gas per operation.

In the results reported in Figure 9 baseline BL1 (B2) has its Gas decreased (increased) as the workload shifts from write-intensive to read-intensive. There is a crossover between BL1 and BL2 when the workload’s read-to-write ratio is around 2. GRuB’s Gas is slightly higher than BL2 for the read-to-write ratio smaller than 2, and is slightly higher than BL1 for the ratio larger than 2. Note that adaptively making the replication decisions with lower Gas between BL1 and BL2 constitutes a Gas-optimal dynamic-replication scheme. In this sense, GRuB’s (converged) Gas is close to the optimal case. Comparing with the two dynamic-replication baselines,
GRuB saves Gas significantly. Especially for read-intensive workloads, the Gas savings by GRuB reach an order of magnitude.

5.1.2 The Choice of Algorithm

In this experiment, we evaluate how the choice of algorithms affect GRuB’s Gas. Recall that we proposed two decision-making algorithms and they differ in that the memoryless (memorizing) algorithm makes the decision without (with) remembering the historical operations. To contrast the two algorithms to the maximal degree, we use the following experimental setting: We set parameter $K = K'$ and use the workload of read-to-write ratio $K + 1$. We drive the workload to GRuB with the two different algorithms. Figure 10(b) reports the Gas per operation along with the timeline (indexed by transactions, each encoding 32 operations). It can be seen that GRuB with the memoryless algorithm incurs constant Gas, that is about 5 times higher than the optimal offline decision-making (whose Gas is calculated in a similar way with the previous experiment in §5.1.1). GRuB with memorizing algorithm, configured with $K' = 8, D = 1$, initially has the similar level of Gas consumption with memoryless GRuB, and then gradually reduces the Gas close to the optimal algorithm.

5.1.3 Parameter $K$

We additionally measure the Gas of memoryless GRuB with varying value of $K$. Recall that $K$ states the threshold number of reads to flip the algorithm’s decision to replication $R$. In the experiment, we drive workloads of varying read-to-write ratios and report the Gas per operation under different values of $K$. In the experiment result in Figure 10(a) given a fixed workload (say read-to-write ratio being 2), the Gas first increases with $K$, then decreases and finally stays at a constant value. The highest Gas represents the worst case that the Gas paid for data replication does not result in any Gas savings for future data reads. Before the peak Gas, increasing $K$ results in increased Gas (due to more off-chain reads and more transactions). After the peak Gas, increasing $K$ results in decreased Gas (due to that off-chain reads are capped in the workload). With different workloads, the value of $K$ under the peak Gas increases along with the read-to-write ratios.

5.1.4 Record Size

In this experiment, we evaluate how GRuB’s Gas is affected by data record size. We vary the record size from one word (32 bytes) to 16 words. The experiment results reported in Figure 10(c) show that Gas per operation increases linearly with the record size. GRuB is cheaper in Gas than both BL1 and BL2. When the record is of 16 words, the Gas savings by GRuB reach the max, that is, $7 \times$ and $3 \times$ compared to BL1 and BL2, respectively.

5.2 Macrobenchmarks on YCSB

In this experiment, we evaluate the gas cost of GRuB under YCSB workloads. In particular, we modified the read/write portion in workload E to generate three sequences of operations, containing 5%, 80%, 5% reads respectively. We use the memoryless algorithm in GRuB and compare its gas cost with the strategy of always replicating data (Baseline BL1), and the strategy of never replicating data (Baseline BL2). Here the reported metric is the average gas cost of operations in a read-write sequence. Here, a read-write sequence is defined to be such that it starts with consecutive writes followed by consecutive read operations. The result, presented in Figure 11, shows that in the first phase, namely from sequence 1 to sequence 65, when the sub-workload contains 5% reads, the gas cost of GRuB is similar to the cost of BL2. The costs of both schemes are $1/5$ of that of BL1. In this write-intensive phase, BL2 is optimal, and our GRuB online algorithm consistently produces the $NR$ decisions, similar to the optimal BL2. In the second phase where the trace contains 80% reads (from sequence 66 to sequence 135), the online algorithm in GRuB makes decisions $R$, and achieves the Gas cost $1/8$ of that of BL2. Compared with BL1, which is the optimal scheme in this phase, GRuB’s cost decreases and then stops at two times of the cost of BL2. In the third phase,
the sub-workload has a similar read portion with the first phase. The gas costs of the three schemes are similar in the beginning and after convergence, GRuB achieves similar gas costs with BL2, and the gas costs of both schemes are 1/5 of that of BL1. The experiment shows the effectiveness of GRuB adapting to a changing workload.

6. RELATED WORK

Blockchain and decentralized applications: Among different Blockchain models, this work focuses on the public Blockchain that runs over an open-membership P2P network. Private Blockchains and privacy-preserving Blockchains are out of scope.

Public Blockchains have been used as a foundational building block to support decentralized applications in finance, supply-chains [14], information-security [16], [17], and other domains. Public Blockchains are used as the source of randomness [32], as trusted clock [31], to support cryptocurrency-backed assets [19], to enable trusted log operations, etc. In particular, there are two Blockchain applications of particular interest to GRuB: 1) Blockchain logging, and 2) token contracts. In Blockchain logging, an off-chain InfoSec system is monitored, producing log entries stored or digested by the Blockchain. Keybase is an encrypted file-sharing application, which maintains a public-key directory for key distribution and uses Bitcoin transactions to witness the directory operations. Catena is a Bitcoin logging scheme that supports lightweight log auditing without downloading the full Bitcoin transaction history. Blockchain-based logging, as in both Catena and Keybase, can prevent log forging attacks without gossiping.

Blockchain scalability and cost-effectiveness: Scalability, in supporting a large volume of transactions, is a known issue in public Blockchains. Research works on Blockchain protocol analysis [21] show that the Blockchain scalability is fundamentally constraint by the limited network resources, resulting in small blocks [21]. Improvements of the Blockchain scalability can be classified into two general approaches: 1) Rebuilding the Blockchain protocol, by reducing the degree of data replication and sharding the Blockchain networks [28], [29], and 2) Reducing the use of Blockchains via various off-chain protocols, also known as Layer-2 protocols. In particular, off-chain payment channels and networks, notably Lightning Networks [12] and others [31], [31], are proposed to batch a series of micro-payments into one Bitcoin transaction, and some have been deployed in real Bitcoin networks. To optimize the Gas of a smart contract, Gasper [18] takes a compiler-oriented approach, namely by detecting Gas-inefficiency anti-pattern in smart contracts. GEM2 tree [40] and TPAD [35] are authenticated data structures tailored to the Gas cost model, by trading expensive on-chain storage for cheaper off-chain computations.

Adaptive Data Replication: In distributed database, adaptive data replication [38], [26], [25] has been studied: A framework has been proposed by dynamically monitoring the workload and making replication decisions based on the current workload. Many web applications exhibit skewed data-access patterns. MET [22] is a KV store management system that adapts the system configuration and cloud-resource provisioning to the current workload. In designing P2P-based DNS services, Beehive [33] is a proactive data replication scheme that is tailored for zipf query distribution and achieves the constant look-up cost.

7. CONCLUSION

This work presents GRuB, a dynamic data replication scheme that can adapt to changing workloads and efficiently using the Blockchain storage to save Gas cost. GRuB does to by monitoring the workload read-write trace and runs an online decision making algorithm off the Blockchain to dynamically replicate data from off-chain to the Blockchain. Evaluated by YCSB benchmark, GRuB shows it can save Gas cost significantly when compared with the baseline designs.

APPENDIX

A. ALGORITHM ANALYSIS

We analyze the competitiveness of the online algorithms, that is, the worst-case algorithm complexity compared with that of off-line algorithm.

**Theorem A.1.** Algorithm 2 [Memoryless algorithm] with parameters configured by Equation 2 is 2-competitive w.r.t. the Gas cost.

**Proof.** We first set up the stage by considering an ideal offline algorithm with optimal cost. This offline algorithm can know the entire sequence of reads and writes in advance, and learn the cost-optimal decision. For instance, it can check given a write, if there are more than K consecutive reads that occur after it (before the next write). If yes, it can replicate the record at the time of the write, instead of waiting until K reads as in the online algorithm.

For our online algorithm, the worst-case sequence of reads and writes is that every write is followed by exactly K reads. This is the worst-case for our online algorithm because every data replica made by the algorithm is never read, in other words, the cost of replication is paid without saving any cost of follow-up reads. In this worst-case, the cost of our algorithm is K + C_rf + C_w = 2C_w. Note that K = C_w/C_rf. In this case, the cost of the ideal offline algorithm is C_w. Thus, the competitiveness of our online algorithm is 2.

**Theorem A.2.** Algorithm 2, i.e., Memorizing algorithm is \( \frac{4D + 2}{K'} \)-competitive.

**Proof.** We use the same ideal offline algorithm as in proving Theorem A.1.

We consider the following sequence of reads/writes for analyzing the worst-case of our memorizing algorithm. The read/write sequence consists of a series of sub-sequences, where the i-th subsequence is of A_i reads and B_i writes. We will set A_i and B_i such that the algorithm will make “wrong” decisions about data replication: It will decide to replicate the data record when it sees A_i reads, and then not to replicate after seeing the next B_i writes. Because each replication decision is followed by writes, the replica is not being read. In other words, the cost of replication is paid without any cost benefit in serving reads by replica. Each no-replication decision is followed by reads, so the follow-up reads are served at the high cost without data replica. In summary, every decision made by the algorithm does not save the cost of serving the following operations, but still incurs the cost of data replication. In this sense, this sequence serves the worst case of our algorithm.

In the i-th sequence, when the algorithm sees A_i reads, it satisfies the in-equation \((B_1 + B_2 + ... + B_i - 1) \times K' < \leq (A_1 + A_2 + ... + A_i) - D\). When it sees B_i writes, it satisfies the in-equation \((B_1 + B_2 + ... + B_i + 1) \times K' = \leq (A_1 + A_2 + ... + A_i) + D\). Combining the two in-equations, we conclude that \(A_i > 2D, B_i = A_i / K'\).

Finally, the general formula for the i-th sequence is: \(A_i = D = 2D + 1\) when \(i \geq 1, A_i = 2D + 1\) when \(i > 1, B_i = (2D + 1) / K'\).

The cost of the i-th sequence in our algorithm is \(A_i \times C_rf + C_w + (B_i - 1) \times C_w\), and the cost of the ideal offline algorithm is \(C_w\); thus the competitiveness of the memorizing algorithm is \(A_i \times C_rf / C_w + B_i\), since \(C_rf / C_w\) equals \(1 / K'\); the competitiveness is \((4D + 2) / K'\).
B. REFERENCES

[1] Bnb token (on etherscan.io).
[2] Certificate transparency.
[3] Certificate transparency, the internet standards.
[4] Erc-20, https://en.wikipedia.org/wiki/erc-20.
[5] Ethereum improvement proposals (core).
[6] Ethereum mainnet.
[7] Go ethereum (geth).
[8] Google certificate transparency api, https://ct.googleapis.com/skydiver/ct/v1/get-entries?start=20000&end=30000.
[9] Google LevelDB, http://code.google.com/p/leveldb/.
[10] Keybase: https://keybase.io/.
[11] Known attacks - ethereum smart contract best practices.
[12] Lightning network, scalable, instant bitcoin/blockchain transactions: https://lightning.network.
[13] List of erc20 tokens on ethereum, https://etherscan.io/tokens.
[14] Maersk and ibm introduce tradelens blockchain shipping solution.
[15] Ropstern testnet in ethereum.
[16] M. Ali, J. C. Nelson, R. Shea, and M. J. Freedman. Blockstack: A global naming and storage system secured by blockchains. In A. Guliati and H. Weatherspoon, editors, 2016 USENIX Annual Technical Conference, USENIX ATC 2016, Denver, CO, USA, June 22-24, 2016., pages 181–194. USENIX Association, 2016.
[17] J. Bonneau. Ethiks: Using ethereum to audit a CONIKS key transparency log. In Clark et al. [19], pages 95–105.
[18] T. Chen, X. Li, X. Luo, and X. Zhang. Under-optimized smart contracts devour your money. In IEEE 24th International Conference on Software Analysis, Evolution and Reengineering, SANER 2017, Klagenfurt, Austria, February 20-24, 2017, pages 442–446, 2017.
[19] J. Clark, S. Meiklejohn, P. Y. A. Ryan, D. S. Wallach, M. Brenner, and K. Rohloff, editors. Financial Cryptography and Data Security - FC 2016 International Workshops, BITCOIN, VOTING, and WAHC, Christ Church, Barbados, February 26, 2016, Revised Selected Papers, volume 9604 of Lecture Notes in Computer Science. Springer, 2016.
[20] B. F. Cooper, A. Silberstein, E. Tam, R. Ramakrishnan, and R. Sears. Benchmarking cloud serving systems with ycsb. In SoCC, pages 143–154, 2010.
[21] K. Croman, C. Decker, I. Eyal, A. E. Gencer, A. Juels, A. E. Kosba, A. Miller, P. Saxena, E. Shi, E. G. Sirer, D. Song, and R. Wattenhofer. On scaling decentralized blockchains - (A position paper). In Clark et al. [19], pages 106–125.
[22] F. Cruz, F. Maia, M. Matos, R. Oliveira, J. Paulo, J. Pereira, and R. Vilaça. Met: workload aware elasticity for nosql. In Eighth Eurosys Conference 2013, EuroSys ’13, Prague, Czech Republic, April 14-17, 2013, pages 183–196, 2013.
[23] I. Eyal and E. G. Sirer. Majority is not enough: Bitcoin mining is vulnerable. In FC 2014, Christ Church, Barbados, pages 436–454, 2014.
[24] E. Heilman, A. Kendler, A. Zohar, and S. Goldberg. Eclipse attacks on bitcoin’s peer-to-peer network. In Jung and Holz [27], pages 129–144.
[25] Y. Huang, A. P. Sistla, and O. Wolfson. Data replication for mobile computers. In Proceedings of the 1994 ACM SIGMOD International Conference on Management of Data, Minneapolis, Minnesota, USA, May 24-27, 1994., pages 13–24, 1994.
[26] Y. Huang and O. Wolfson. A competitive dynamic data replication algorithm. In Proceedings of the Ninth International Conference on Data Engineering, April 19-23, 1993, Vienna, Austria, pages 310–317, 1993.
[27] J. Jung and T. Holz, editors. 24th USENIX Security Symposium, USENIX Security 15, Washington, D.C., USA, August 12-14, 2015. USENIX Association, 2015.
[28] E. Kokoris-Kogias, P. Jovanovic, L. Gasser, N. Gailly, E. Syta, and B. Ford. Omniledger: A secure, scale-out, decentralized ledger via sharding. In 2018 IEEE Symposium on Security and Privacy (SP), volume 00, pages 19–34.
[29] L. Luu, V. Narayanan, C. Zheng, K. Baweja, S. Gilbert, and P. Saxena. A secure sharding protocol for open blockchains. In E. R. Weippl, S. Katzenbeisser, C. Kruegel, A. C. Myers, and S. Halevi, editors, Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security, Vienna, Austria, October 24-28, 2016, pages 17–30. ACM, 2016.
[30] M. S. Melara, A. Blankstein, J. Bonneau, E. W. Felten, and M. J. Freedman. CONIKS: bringing key transparency to end users. In Jung and Holz [27], pages 383–398.
[31] A. Miller, I. Bentov, R. Kumaresan, and P. McCorry. Sprites: Payment channels that go faster than lightning. CoRR, abs/1702.05812, 2017.
[32] A. Narayanan, J. Bonneau, E. W. Felten, A. Miller, and S. Goldfeder. Bitcoin and Cryptocurrency Technologies - A Comprehensive Introduction. Princeton University Press, 2016.
[33] V. Ramasubramanian and E. G. Sirer. Beehive: O(1) lookup performance for power-law query distributions in peer-to-peer overlays. In 1st Symposium on Networked Systems Design and Implementation (NSDI 2004), March 29-31, 2004, San Francisco, California, USA, Proceedings, pages 99–112, 2004.
[34] Y. Tang, Z. Xing, C. Xu, J. Chen, and J. Xu. Lightweight logging over the blockchain for data-intensive applications. In 2nd Workshop on Trusted Smart Contracts at International Conference on Financial Cryptography and Data Security, Santa Barbara Beach Resort, Curacao, Mar. 2018.
[35] Y. Tang, Z. Xing, C. Xu, J. Chen, and J. Xu. Lightweight blockchain logging for data-intensive applications. In A. Zohar, I. Eyal, V. Teague, J. Clark, A. Bracciali, F. Pintore, and M. Sala, editors, Financial Cryptography and Data Security - FC 2018 International Workshops, BITCOIN, VOTING, and WTSC, Nieuwpoort, Curacao, March 2, 2018, Revised Selected Papers, volume 10958 of Lecture Notes in Computer Science, pages 308–324. Springer, 2018.
[36] A. Tomescu and S. Devadas. Catena: Efficient non-equivocation via bitcoin. In 2017 IEEE Symposium on Security and Privacy, SP 2017, San Jose, CA, USA, May 22-26, 2017, pages 393–409. IEEE Computer Society, 2017.
[37] P. Tsankov, A. M. Dan, D. Drachsler-Cohen, A. Gervais, F. Bünzli, and M. T. Vechev. Secure: Practical security analysis of smart contracts. In Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security, CCS 2018, Toronto, ON, Canada, October 15-19, 2018, pages 67–82, 2018.
[38] O. Wolfson, S. Jajodia, and Y. Huang. An adaptive data replication algorithm. ACM Trans. Database Syst., 22(2):255–314, 1997.
A. Zamyatin, D. Harz, J. Lind, P. Panayiotou, A. Gervais, and W. J. Knottenbelt. XCLAIM: trustless, interoperable, cryptocurrency-backed assets. In 2019 IEEE Symposium on Security and Privacy, SP 2019, San Francisco, CA, USA, May 19-23, 2019, pages 193–210, 2019.

C. Zhang, C. Xu, J. Xu, Y. Tang, and B. Choi. Gem2-tree: A gas-efficient structure for authenticated range queries in blockchain. In 35th IEEE International Conference on Data Engineering, ICDE 2019, Macao, China, April 8-11, 2019, pages 842–853. IEEE, 2019.

F. Zhang, P. Daian, I. Bentov, and A. Juels. Paralysis proofs: Safe access-structure updates for cryptocurrencies and more. IACR Cryptology ePrint Archive, 2018:96, 2018.